ANALYSIS AND VISUALISATION OF VERY-LONG-DURATION ACOUSTIC RECORDINGS OF THE NATURAL ENVIRONMENT

Yvonne Fiona Phillips

B.AppSc (Physics) (Central Queensland University)

B.LandArch First class Honours (Queensland University of Technology)

Submitted in fulfilment of the requirements for the degree of
Doctor of Philosophy (Research)

Science and Engineering Faculty
School of Electrical Engineering and Computer Science
Queensland University of Technology

2018

Keywords

Acoustic indices, Anthropophony, Bioacoustics, Biophony, Cicadas, Clustering, Data reduction, Diel plots; Dot-matrix plots, Ecoacoustics, Ecological Monitoring, Geophony, Long-duration false-colour spectrograms, Microphone malfunction, Principal Components Analysis, Soundscape Ecology, Very-long-duration audio recording, Visualisation.

Abstract

Advances in technology and reduction in data storage costs enable the autonomous collection of large quantities of continuous audio recordings. While the collection of very long environmental recordings has become easier, the analysis of these recordings remains challenging. A very-long-duration audio recording is defined as one with a minimum length of one day, but may have durations of weeks, months, or years. This thesis provides methods for data reduction and visualisation that enable the ecological interpretation and navigation of very-long-duration audio recordings.

The major theme of data reduction commenced after the establishment of protocols and the collection of two thirteen-month continuous audio recordings from two separate Southeast Queensland forest ecosystems. The acoustic indices calculated on one-minute audio segments were used to develop two new techniques to visualise the contents of very-long-duration recordings. An acoustic index is a mathematical expression used to measure a particular aspect of the energy distribution in audio recordings. Microphone failure in one channel was noticed shortly after the recording commenced. A method was established to detect microphone problems in long recordings.

A novel error measure was developed to detect seasonal and site differences and enable optimisation of the clustering based on seasonal and site differences in the data. Cluster interpretation on very-long-duration audio recordings is problematic because listening to large amounts of audio is time-consuming and therefore impractical. To overcome this, a series of five methods were developed to build on the interpretations made through listening. These methods enabled the allocation of an acoustic label to each cluster, resulting in a labelled acoustic sequence. This acoustic sequence was used to develop three additional visualisation techniques.

The culmination of the methods developed in this thesis was the six case studies. These extended the ecological interpretation of the acoustic sequence beyond those that were made through the visualisations. The case studies demonstrated that clustering can facilitate ecological interpretation of very-long-duration audio recordings.

Table of Contents

List of Figures

List of Tables

List of Publications

The publications with myself as the first author include one academic journal, a conference paper and a refereed abstract.

Journal papers

1. **Phillips, Y.F.**, Towsey, M. & Roe, P. (2018). Revealing the Ecological Content of Long-duration Audio-recordings of the Environment through Clustering and Visualisation. *Plos One*, 13(3), e0193345. doi:10.1371/journal.pone.0193345.

This thesis uses clustering for data reduction allowing the visualisation of the contents of very-long duration acoustic recordings. This paper discussed the evaluation of four clustering methods and provided an interpretation of the clustering result. Three visualisation techniques, the PCA diel plot, Polar Histograms and Cluster diel plots are introduced which are used to visualise the seven acoustic classes identified in the data.

Conference paper

2. **Phillips, Y.F.**, Towsey, M., & Roe, P. (2017, 7-10 November). Visualization of environmental audio using ribbon plots and acoustic state sequences. Paper presented at the IEEE International Symposium on Big Data Visual Analytics (BDVA), Adelaide, Australia. doi. 10.1109/bdva.2017.8114628.

This paper introduces three visualisation techniques for displaying the contents of long-duration audio recordings, the ribbon plot, composite false-colour spectrograms and dot-matrix plots.

Refereed abstract

3. **Phillips, Y.F.**, Towsey, M. & Fuller, S. (2018, 24-28 June). Acoustic structure in the dawn bird and dawn and dusk cicada choruses. 2018 Ecoacoustics Congress. Brisbane, Australia.

The presentation discussed two case studies, the structure of the dawn bird chorus and the dawn and dusk cicada chorus. The case studies use the cluster sequence to enable ecological interpretation of the changes in the bird and cicada choruses across days and seasons.

Other publications include two academic papers and one refereed abstract in which I was not the first author. These are provided below.

Journal papers

4. Towsey, M., Znidersic, E., Broken-Brow, J., Indraswari, K., Watson, D.M., **Phillips, Y.F.**, Truskinger, A., & Roe, P. (2018). Long-duration, False-colour Spectrograms for Detecting Species in Large Audio Datasets. *Journal of Ecoacoustics*, 2, doi:10.22261/JEA.IUSWUI.

This paper discusses the use of ribbon plots in finding bat calls in long-duration recordings.

5. Kholghi, M., **Phillips, Y.F.**, Towsey, M. Sitbon, L. & Roe, P. (2018). Active Learning for Classifying Long Duration Audio Recordings of the Environment. *Methods in Ecology and Evolution,* 00, 1-11, doi:10.1111/2041-210x.13042.

This paper corresponds to ongoing work being conducted on the data collected in this research in relation to the classification of minutes within long-duration recordings.

Refereed abstract

6. Towsey, M. Roelofs, A., **Phillips, Y.F.**, Truskinger, A. & Roe, P. (2018, 24-28 September). Content description of Very-long-duration Recordings of the Environment. 10th International Conference on Ecological Informatics. Jenna, Germany.

This presentation will discuss ongoing work beyond this thesis.

List of Abbreviations and Terms

General Terms

FFT	Fast Fourier transform (Cooley & Tukey, 1965)
I3DD	Intra-three-day-distance
LDFC	Long-duration False-colour (in relation to spectrograms) (Towsey et al., 2018b)
PCA	Principal Components Analysis (Hotelling, 1933; Pearson, 1901)
RGB	Red, green, blue image channels
SM2+	Song Meter 2+ acoustic recorder (Wildlife Acoustics, 2013)
STFT	Short-time Fourier transform (Schafer & Rabiner, 1973)

Acoustic Indices

ACI	Acoustic Complexity Index (Pieretti, Farina & Morri, 2011)
ACT	Activity (Towsey, 2017)
AEI	Acoustic Evenness Index (Villanueva-Rivera, Pijanowski, Doucette & Pekin, 2011)
BGN	Background Noise (Lamel, Rabiner, Rosenberg & Wilpon, 1981; Towsey, 2017)
CLC	Cluster Count (Towsey, 2017)
D	Acoustic Dissimilarity Index (Gasc, Sueur, Pavoine, Pellens & Grandcolas, 2013b)
EAS	Entropy of Average Spectrum (Towsey, 2017)
ECV	Entropy of Coefficient of Variation (Towsey, 2017)
ENT	Temporal Entropy (Sueur, Pavoine, Hamerlynck & Duvail, 2008).
EPS	Entropy of Peaks Spectrum (Towsey, 2017)
EVN	Events per Second (Towsey, 2017)
HFC	High Frequency Cover (Towsey, 2017)
LFC	Low Frequency Cover (Towsey, 2017)
MFC	Mid Frequency Cover (Towsey, 2017)
NDSI	Normalised Difference Soundscape Index (Kasten, Gage, Fox & Joo, 2012)
SNR	Signal-to-Noise ratio (Towsey, 2017)
SPT	Spectral Peak Tracks (Towsey, 2017)
ZCR	Zero Crossing Rate

Algebraic symbols

A	spectral amplitudes (Fourier coefficients)
α	power spectral density of sounds in 1-2 kHz range
β	power spectral density of sounds in 2-11 kHz range
f	frequency bin
k	frame index
n	number of frames
N	number of frequency bins
pmf	probability mass function

Glossary

abiotic	Not biological. Physical environmental factors such as wind, temperature, rain and air pressure.
civil dawn	The time before sunrise corresponding to when the sun is six degrees below the horizon.
civil dusk	The time after sunset corresponding to when the sun is six degrees below the horizon.
data reduction	A process that groups or summarises data (Friel, Bright, Frierson & Kader, 1997). Common forms include clustering and Principal Components Analysis (PCA).
ecology	The study of the flow of water, nutrients and energy in an area and how the organisms living within the area interact with these flows (Jordan, 1975).
Ecological process	Any action or occurrence that supports the long-term survival of a species or the biodiversity of an area, for example long-range migration (McQuillan, Watson, Obendorf, Fitzgerald & Leaman, 2009).
orthoptera	Orthopteran species include crickets, katydids, grasshoppers and locusts.

Statement of Original Authorship

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

Signature: QUT Verified Signature

Date: November 2018

Acknowledgements

I would like to sincerely thank my supervisors Professor Paul Roe and Dr Michael Towsey for believing in me. Professor Paul Roe reminded me that I needed to know my data and to keep sight of the big picture. This led to me learning the calls of the bird, mammal, and cicada species in the audio recording. This was not easy considering how few birdcalls I knew at the commencement. To Dr. Michael Towsey thank you, the thesis is richer for your generosity and guidance, your help was invaluable.

I would also like to thank Anthony Truskinger who performed the Audio Analysis on the very-long-duration audio recording to calculate the summary and spectral acoustic indices.

I would also like to thank Kelvin and Amelia Nielsen for verifying the birdcalls that I annotated and for showing me how to bird watch. Thank you also to Tom Tarrant and Dez Wells for helping me to get started on recognising birdcalls in recordings.

Chapter 1

Introduction

This thesis presents research into the collection and the analysis of *very-long-duration audio recordings* for improving the interpretation of ecological content and navigation of these recordings. A very-long-duration audio recording is defined as one with a minimum length of one day, but may extend to weeks, months, or years. They are recordings that have been collected continuously, not ones that have been sampled. These recordings are very interesting to work with because they enable the study of patterns at daily and seasonal scales. The use of autonomous field-ready audio recorders, a recent development, has enabled the ease of collection of large volumes of audio data. Comprehensive manual annotation, the labelling of the vocalisations of individual species and other sound events, is not possible or prohibitively time-consuming in long recordings (Brighten, 2015; Fairbrass, Rennett, Williams, Titheridge & Jones, 2017; Ganchev, 2017; Kershenbaum et al., 2016; Potamitis, 2014). Other forms of analysis are needed and the use of visualisation will play an important role in the analysis of very-long-duration audio recordings.

This chapter provides the background, motivation for the research, research problem, research hypothesis, objectives, and the contributions and significance of the research.

1.1 BACKGROUND

During the 100-year history of Bioacoustics, audio recorders have become significantly smaller and easier to use, and more field ready. The storage capacity of today's recorders allows their placement in the environment unattended for months, unobtrusively recording all sounds. In addition to the ease of continuous recording, there is an increasing interest from researchers, ecologists, and government agencies in the capacity of audio recordings to monitor the environment. Acoustic recordings are possibly unique in enabling access to animal community dynamics within one methodology. However, long-duration audio recordings, that is, those longer than about one day are time-consuming to process by listening in real time and manual annotation of all species in long recordings is not possible or highly impractical.

The ease of obtaining field recordings has driven the collection of large quantities of environmental audio, days, months, and even years in duration. Such recordings are ‘opaque’ because there is too much to listen to and listening to audio can be fatiguing (Jinnai, Boucher, Robertson & Kleindorfer, 2010; Mortimer & Greene, 2017). In recent years, long-duration, false-colour (LDFC) spectrograms have been developed to visualise rather than listen to audio recordings (Towsey et al., 2014b). Although it may seem counterintuitive, visualisation rather than listening is the key to the interpretation of long audio recordings. This is because our eyes have the ability to quickly scan for patterns at multiple temporal scales (Shneiderman, 1996).

Grey-scale spectrograms, invented more than seventy years ago, remain the preferred method to visualise short-duration audio, that is, on the scale of minutes. However, they are ineffective for viewing audio segments longer than several hours. LDFC spectrograms, having a resolution of one-minute per spectrogram frame, meet the need for viewing audio segments with a duration from several minutes to several days. However, there are currently no effective techniques to visualise audio recordings longer than 2-4 days (see Figure 1.1). The aim of this research is to develop visualisation, interpretation and navigation techniques appropriate for very-long-duration recordings of the environment, that is, for recordings having lengths of weeks, months, and years.

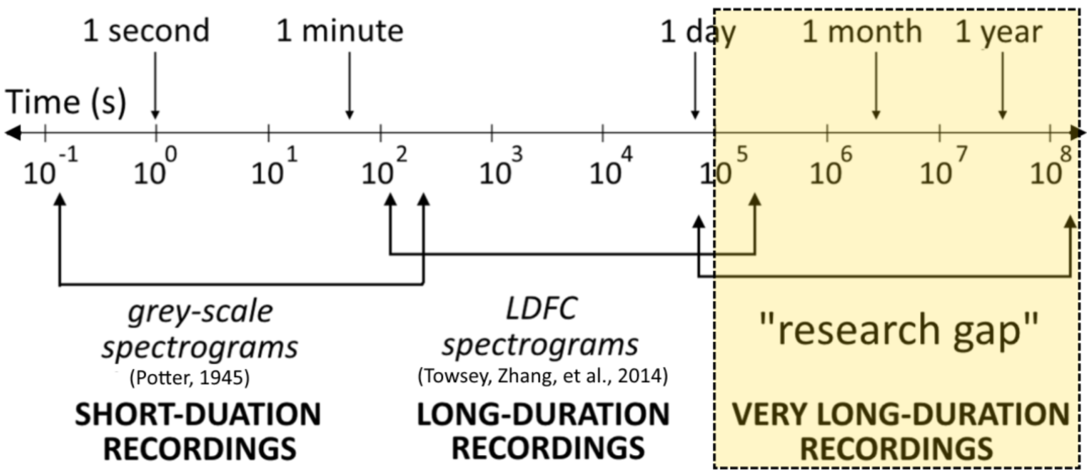


Figure 1.1 The time scale of audio recordings from short-duration recordings to the length of very-long audio recordings, illustrating the current visualisation techniques, grey-scale spectrograms and long-duration false-colour (LDFC) spectrograms. There are no existing visualisation techniques that allow the easy interpretation of very-long-duration audio recordings.

All techniques to visualise audio recordings require some form of data reduction. The Fast Fourier transform (FFT) used to produce the ‘standard’ grey-scale spectrogram reduces the data by one-half. LDFC spectrograms achieve data reduction of three-orders of magnitude (Towsey et al., 2014b). To visualise very-long audio recordings, increased data reduction will be necessary. Data reduction is therefore an important theme in this research.

1.2 MOTIVATION

The extraction of information from long-duration recordings is dependent on automated methods because manual processing is difficult (Gasc, Pavoine, Lellouch, Grandcolas & Sueur, 2015) and prohibitively expensive in time (Fairbrass et al., 2017) and money. Some progress has been made with automated navigation and visualisation of long-duration recordings up to a few days in length. There is however, an absence of automated analysis including visual analytics techniques to cater for very-long-duration recordings.

1.3 RESEARCH PROBLEM

Recent developments in information technologies have allowed the collection of large amounts of acoustic recordings exceeding the capacity of ecologists to listen to them. Finding ways to increase the transparency of long-duration recordings and improve navigation is required in order to increase the amount and broaden the type of information that is extracted from these recordings.

The research problem is posed primarily by the temporal and computational scale of what is being attempted. To the best of the author's knowledge, the collection, analysis, and visualisation of the content of more than one year of continuous terrestrial environmental recordings has not been attempted previously. In addition, for the analysis of large quantities of audio to have relevance, it must be demonstrated that the methods developed yield ecological insights. New methodologies, particularly in the area of data-reduction and visualisation, will have to be developed, since there is a limit to how the current LDFC spectrogram techniques can be scaled up.

1.4 RESEARCH HYPOTHESIS

This research is positioned in relation to the following research hypothesis:

Clustering can provide the data reduction necessary for the visualisation of very-long-duration audio recordings to facilitate ecological interpretation and navigation.

This hypothesis is pursued through the following four objectives:

Objective 1 – Acquisition of the audio recording

To acquire a continuous very-long-duration audio recording (of at least 12 months) from two natural forest sites and prepare the data for data reduction (Chapters 4 and 5).

Protocols are to be developed for the collection, storage, and analysis of the very-long-duration recording. The collection of a continuous 24-hour per day audio recording will require a scheduled commitment of time. As microphone malfunction was noted shortly after the collection commenced, a method will also be developed to detect microphone problems.

Objective 2 – Data reduction by clustering

To appraise data reduction methods to determine a method that robustly detects soundscape changes across time and space and apply this to at least one year of continuous audio recordings (Chapters 7 and 8).

Soundscapes undergo gradual changes over time due to seasonal variations in vocalising species and weather. Using generic acoustic features, comparisons can be made across recordings, seasons and sites, which highlight soundscape changes.

Objective 3 – Visualisation techniques

To develop visualisation techniques that allow the interpretation and navigation of very-long-duration audio recordings at different stages of the data reduction process (Chapters 6 and 9).

No visualisation techniques currently exist for the easy interpretation of continuous audio data on the scale of weeks, months, and years. Very-long-duration audio recordings contain data on the scale of many orders of magnitude greater than those of short-duration recordings (see Figure 1.1); as such new visual analytic approaches are needed.

Objective 4 – Ecological interpretation

To evaluate the ecological content that was revealed by the chosen data reduction method (Chapters 8, 9 and 10).

The evaluation of ecological content supports the main aim. It will be evaluated through the process of cluster evaluation and a series of case studies.

1.5 RESEARCH PLAN

Figure 1.2 provides an overview of the research plan. This plan contains four studies; each aligned to one of the four objectives. This section explains the steps involved in the attainment of each objective.

1.5.1 Study 1: Obtain a continuous very-long-duration audio recording and an acoustic feature dataset (Objective 1)

Audio recordings will be collected at two field sites in Southeast Queensland for a period of thirteen-months (Chapter 4). A method will be developed to automatically detect problems with microphones within the recording (Chapter 5). Acoustic indices will be calculated from each one-minute segment of recording (Chapter 4).

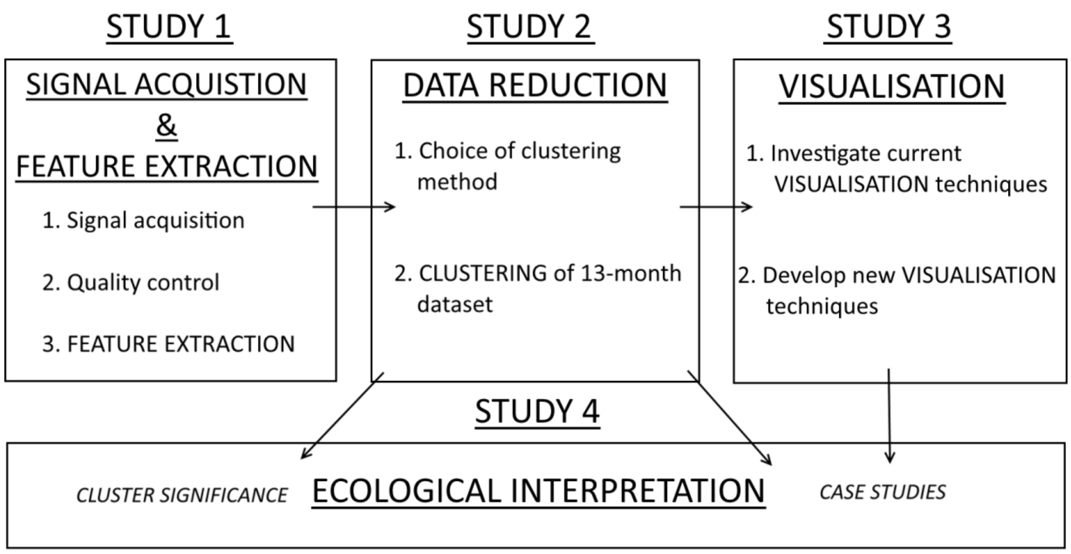


Figure 1.2 The workflow of the four studies to achieve the four objectives.

1.5.2 Study 2: Appraise data reduction methods using a test dataset and choose one that robustly distinguishes ecological difference in the soundscape across time and apply this to the thirteen-month dataset (Objective 2)

Establish a test dataset free of rain and to be representative of the biophony of the two sites. Apply four clustering methods to the test dataset to choose one that most robustly separates the different biophonies (Chapter 7). Apply the best clustering method to the thirteen-month dataset. Interpret the clusters produced by the clustering of the thirteen-month dataset to provide labels for the clusters (Chapter 8).

1.5.3 Study 3: Visualise acoustic data at the different stages of data reduction for the purpose of revealing the content of very-long-duration audio recordings (Objective 3)

Review and evaluate current visualisation methods (Chapter 2, Section 2.6) for the purpose of determining the suitability of methods that visualise the content of acoustic recordings. Develop visualisation techniques to visualise the contents of very-long-duration audio recordings that take advantage of various stages of the data reduction process (Chapters 6 and 9).

1.5.4 Study 4: Determine the ecological significance of the data reduction result by performing a series of case studies (Objective 4)

Identify the cluster contents using a combination of methods and allocate each cluster to an acoustic class (Chapter 8). Perform case studies to find patterns or cycles in the labelled acoustic class sequence obtained from the clustering (Chapter 10).

1.6 RESEARCH CONTRIBUTIONS

The contributions of this research are:

1. The establishment of two simultaneous thirteen-month open-source continuous audio recording. doi:10.4225/09/5a7297ee4b893. (Appendix A). These recordings have been subsequently used in other research (page xvi).
2. The development of a method to cluster very-long-duration acoustic recordings and methods for cluster interpretation that reveal the ecological content of the recordings (Chapters 7 and 8).

3. Visualisation techniques for pre- and post- clustering, specifically designed for very-long-duration recordings (Chapters 6 and 9 respectively). The pre-clustering techniques utilise the acoustic features and the post-clustering techniques utilise the labelled acoustic state sequence.
4. I am first author on one research paper, a conference presentation and paper and a refereed abstract and the second or subsequent author on two academic journal papers (Pages xv-xvi).
5. The identification and verification of the calls of 80 bird species and 3 mammal species (Appendix B) and over 8000 bird call annotations on the Ecosounds website (Truskinger, Cottman-Fields, Eichinski, Towsey & Roe, 2014).

1.7 RESEARCH SIGNIFICANCE

This research provides a practical method for the analysis of very-long-duration audio recordings. In practice, this will enable the visualisation and improved navigation and understanding of environmental audio recordings.

The significance of this research is that it:

1. Establishes and demonstrates a data reduction method to facilitate ecological interpretation of very-long-duration audio recordings.
2. Develops and validates new visualisation techniques for the interpretation of ecological content within very-long-duration audio recordings.
3. Makes available the data, audio recording, and computer code for future research into the ecological interpretation of very-long-duration audio recordings.

1.8 SUMMARY

Motivated by the amount of ecological information contained in very-long-duration audio recordings and the impracticality of manual annotation, this research focuses on the development of data reduction and visualisation techniques to facilitate the interpretation and navigation of these recordings.

Visualisation has been used to assist in the interpretation of the contents of audio recordings for at least seventy years. However, there are no current visualisation techniques that display the contents of very-long-duration audio recordings; this is where a research gap exists.

Chapter 2

Literature Review and Background

2.1 OVERVIEW

This literature review is structured into seven themes. The first two themes provide the background, the next four are aligned to the four studies (Chapter 1) and the final theme examines additional analytical techniques used to automatically recognise species:

1. *Bioacoustics*, the traditional research field that focuses on the vocal behaviour of individuals or single species (Section 2.2).
2. *Soundscape Ecology and Ecoacoustics*, the new scientific fields (Pijanowski et al., 2011b; Sueur & Farina, 2015) introduced in 2011 and 2015 respectively to account for the changing nature of the use of audio recordings in ecological research (Section 2.3).
3. *Protocols for the Collection of Audio Recordings* (Section 2.4).
4. *Data Reduction for Environmental Acoustic Recordings.* What are the current data reduction techniques used in acoustics? What are the challenges of using these techniques? (Section 2.5).
5. *Acoustic Visualisation*, What are the current techniques? (Section 2.6).
6. *Ecological Interpretation.* What is being interpreted from acoustic recordings and what ecological questions are being answered? (Section 2.7).
7. *Analytical Techniques for Environmental Acoustic Recordings.* What techniques have been developed for automatic species recognition? (Section 2.8).

The scope of this literature review is research related to terrestrial environments in the human hearing range (20 Hz to 20 kHz), ultrasonics is not included.

2.2 BIOACOUSTICS

Bioacoustics, the traditional study of the acoustic behaviour of vocalising animals, is concerned with how animals communicate (Fletcher, 2007). Species of birds, frogs and insects produce the most common biotic sounds in natural environments (Pijanowski et al., 2011b). Birds are particularly vocal during the morning chorus (Staicer, Spector & Horn, 1996, p.426) and at dusk (Malavasi & Farina, 2013) along with some insects including some species of cicadas (Doolan & Mac Nally, 1981). Frogs and insects call at dusk and during the night (Kacelnik & Krebs, 1982; Mazaris, Kallimanis, Chatzigianidis, Papadimitriou & Pantis, 2009). Vocalisations have a range of functions, territorial defence, socialisation, and warning of the presence of predators (Blumstein et al., 2011; Gerhardt, 1994; Roy & Elepfandt, 1993; Slabbekoorn & Ripmeester, 2008; Thorne & Shepherd, 2013). Birds, amphibians, insects, and mammals will be briefly reviewed in relation to the sounds they make and the diel and seasonal pattern of their calls.

2.2.1 Birds

Birds tend to communicate through song over large distances 50 to 200 metres, much greater than that of unaided human communication (Wiley & Richards, 1982, p.132). The vocal organ the syrinx and associated muscles produce sound (Ames, 1971, p.138-139) and in some bird species the associated muscles allow very fine and rapid control of sound modulation (Elemans, Mead, Rome & Goller, 2008; Goller & Riede, 2013). Most birdsong occurs in the range of 1-8 kHz (Wiley & Richards, 1982, p.140) which compares well with the hearing range of birds 1-5 kHz (Dooling, 1983, p.101; 2004, p.208-209).

Birds have a greater habitat distribution than any other vertebrate and there are more species of bird than any other terrestrial vertebrate (Brandes, 2008a; Sekercioglu, 2011). Bird vocal communications vary from simple tones to complex songs (Acevedo, Corrada-Bravo, Corrada-Bravo, Villanueva-Rivera & Aide, 2009; Brandes, 2008b; Chen & Maher, 2006) (Figure 2.1) and calls can vary from region to region (Mennill & Rogers, 2006).

The variations in calls make computer based automatic classification difficult (Gasc et al., 2013a; Truskinger et al., 2014). Despite this, recent attempts to use image analysis, for example Potamitis (2014) – see Section 2.5, show promise in being able to identify bird calls from environmental recordings.

Birds can have bimodal calling patterns during the day with inactivity around midday resulting from them avoiding hotter temperatures (Jacquet & Launay, 1997; Reyes-Arriagada, Jiménez & Rozzi, 2015). Insectivorous birds can display unimodal activity being regulated by warmer temperatures when insects are active (Lewis & Taylor, 1965; Reyes-Arriagada et al., 2015).

The bird dawn chorus, a period of intense calling commences as early as ninety minutes before sunrise (Burt & Vehrencamp, 2005, p.320). Light intensity and eye size may affect the start time of the calling of certain bird species (Hall & Ross, 2007; Thomas et al., 2002). Dawn is the most favourable time for sound transmission as the atmospheric conditions allow calls to travel further and cover larger areas (Henwood & Fabrick, 1979).

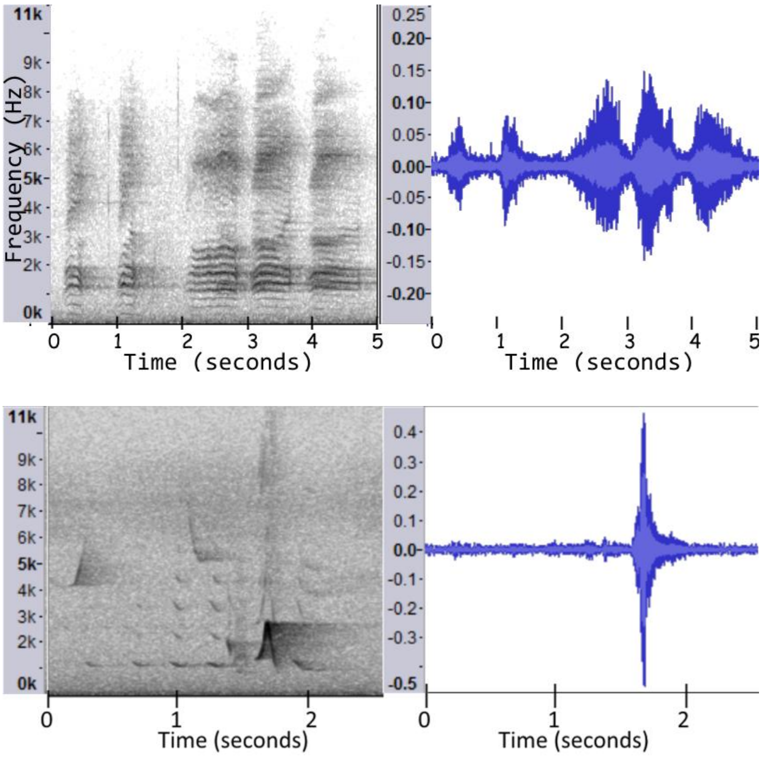


Figure 2.1 The spectrogram and waveform of short segments containing a Torresian Crow (*Corvus orru*) call (top) and a Grey-Shrike-thrush (bottom) call. Bird calls tend to concentrate acoustic energy over short time periods. Images produced using Audacity (Ash et al., 2017).

2.2.2 Amphibians

Frog advertisement calls are common in the 2 to 5 kHz frequency range (Pijanowski et al., 2011b; Roy & Elepfandt, 1993). Larger frogs call at lower frequencies (Fletcher, 2007). Temporal partitioning is common in frogs, individuals remain silent while other species are calling (Gerhardt & Schwartz, 1994 p.604; Zelick & Narins, 1985) although they also call in chorus. Frog calls are generally loud and simple in structure and are easier to identify than birds (Acevedo et al., 2009; Gerhardt, 1994; Roy & Elepfandt, 1993; Toledo et al., 2015).

2.2.3 Insects

Orthoptera (crickets, grasshoppers and katydids) and Hemiptera (cicadas) make up the main groups of sound producing insects (Ganchev, Potamitis & Fakotakis, 2007). Most insects call in the range from 3 to 8 kHz (Pijanowski et al., 2011b), although many species call up to frequencies of 20 kHz or higher (Ferreira et al., 2018; Gasc et al., 2013b; Jeliazkov et al., 2016; Lehmann, Frommolt, Lehmann & Riede, 2014; Potamitis, 2014).

Crickets are heard at night (Figure 2.2) (Pijanowski, Farina, Gage, Dumyahn & Krause, 2011a), however they also call during the day (Ferreira et al., 2018; Gasc, Anso, Sueur, Jourdan & Desutter-Grandcolas, 2017; Otte & Cade, 1983). Cicadas usually call during the day (Pijanowski et al., 2011a), but they also call at dawn and dusk (Doolan & Mac Nally, 1981; Josephson & Young, 1979; Young, 1981) and at night (Ewart & Popple, 2007).

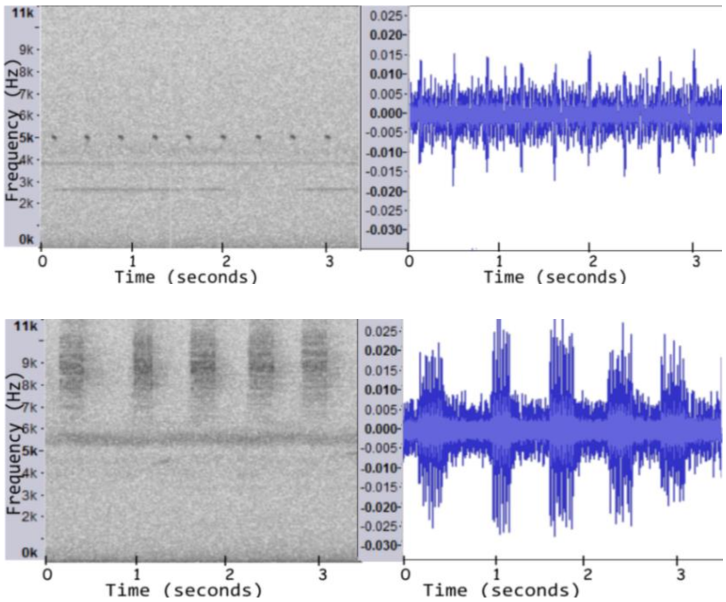


Figure 2.2 The spectrogram and waveform of 3 second segments of two different night-time insect calls. Note the difference in frequency and amplitude of the two sets of calls. Image produced in Audacity (Ash et al., 2017).

The mechanisms for sound production in cicadas and crickets differ. Cicadas use a tymbal mechanism (Fletcher & Hill, 1978; Young, 1981; Young & Bennet-Clark, 1995) and can maintain continuous sounds (Walker, 1962; Young & Josephson, 1983). Crickets and grasshoppers instead make sound by rubbing body parts (Ganchev et al., 2007; Riede, 1998; van Staaden & Römer, 1997).

2.2.4 Mammals

Mammals also vocalise. The male Koala (*Phascolarctos cinereus)* for example bellows (Figure 2.3) to attract females (Ellis et al., 2011). The Grey-headed Flying Fox (*Ptempus poliocephalus*) has five different call types (Christesen & Nelson, 2000). The White-striped Free-tailed Bat (*Austronomus australis*) has an echolocation call with a frequency low enough to be heard by humans (Griffiths, 2013). Other mammals that vocalise include the Sugar Glider (*Petaurus breviceps*), bandicoots (Van Dyck, 1995 p.288) and the Common Brushtail Possum (*Trichosurus vulpecula)* (Winter, 1976 p.41-91). Many of these species are in the vicinity of one of the sites where recordings were made for this research (Queensland Government, 2015c).

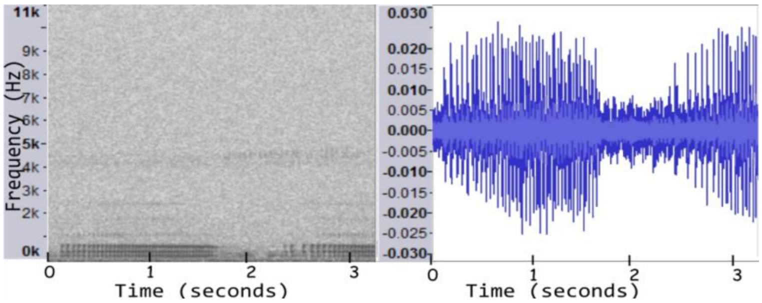


Figure 2.3 The spectrogram and waveform of a 3-second segment containing the mating call of the male Koala. Image produced using Audacity (Ash et al., 2017).

2.2.5 Vocal Species as Ecological Indicators

Birds, amphibians and insects provide the basis for the use of acoustic recordings as a valuable tool for monitoring ecosystem health (Tucker, Gage, Williamson & Fuller, 2014). Birds are of interest because they are widespread, are cost-efficient to monitor, vocalise over long distances and their behaviour and biology is well understood (Bardeli et al., 2010; Eglington, Noble & Fuller, 2012; Gregory & van Strien, 2010; Larsen, Bladt, Balmford & Rahbek, 2012; Peck et al., 2014). The Cuckoo (*Cuculus canorus*) is a good indicator of bird species richness and is easy to detect using acoustics (Tryjanowski & Morelli, 2015). Other taxa such as insects are good environmental indicators (Brandes, Naskrecki & Figueroa, 2006; Gasc et al., 2017; Lehmann et al., 2014; Riede, 1998) and frogs indicate stream quality (Welsh & Ollivier, 1998).

2.2.6 Signal Degradation

Animal calls convey information through encoding by the sender, transmission through a medium and detection by a receiver (Forrest, 1994). The transmission of calls is affected by attenuation and degradation (Tobias et al., 2010; Wiley & Richards, 1978). Attenuation, the loss of intensity of a call, occurs as the sound spreads spherically out from the source decreasing at a minimum rate of 6 dB for each doubling of distance (Forrest, 1994). Additional excess attenuation occurs as sound waves interacts with objects in the natural environment including ground surface, vegetation and temperature gradients (Morton, 1975). In general, low frequency calls experience less attenuation and usually transmit further than high frequency calls (Naguib & Wiley, 2001; Wiley & Richards, 1982, p.148). As a result, assumptions about sound transmission are not straightforward.

Both reverberation caused by reflections and amplitude fluctuations caused by air movement reduce signal quality (Wiley & Richards, 1982, p.152). Strong wind is particularly detrimental to acoustic communication (Wiley & Richards, 1978, p.78) because strong wind occupies acoustic space across the broadband spectrum (Gage & Axel, 2014).

A shadow zone caused by the upward refraction of sound reduces horizontal sound transmission. While the reflection of sound from the tree canopy improves horizontal transmission (Morton, 1975). These effects have direct implications for animal communication (Forrest, 1994) and for sound recording. Mornings are the best time for sound to be transmitted (Henwood & Fabrick, 1979), and middays the worst, due to wind (Wiley & Richards, 1982, p.162). The analysis and interpretation of audio recordings requires a working knowledge of the limitations of sound transmission.

The increased availability of environmental recordings has encouraged the recent move from a single species focus to a community and soundscape focus (Pijanowski et al., 2011b). This has caused a shift towards monitoring methods developed in the fields of Soundscape Ecology and Ecoacoustics and a move away from manual annotation towards automated methods using acoustic indices.

2.3 SOUNDSCAPE ECOLOGY AND ECOACOUSTICS

Soundscape Ecology is the study of the relationships between the sounds in a landscape and the human and nature-based processes responsible for them (Pijanowski et al., 2011b). The soundscape is “the complete acoustic environment” (Blumstein et al., 2011 p.759) or all sounds in a landscape originating from three sound sources: biophonies, geophonies and anthropophonies (Pijanowski et al., 2011a). Biophonies consist of all sounds originating from animals, including the vocalisations of birds, amphibians and mammals and the calls of insects (Joo, Gage & Kasten, 2011). Geophony (Figure 2.4) originates from physical processes for example rain, wind and thunder but also sounds associated with flowing water and earth movements (Pijanowski et al., 2011a). Anthropophony is inclusive of all sounds associated with human activities, both cultural and mechanical sounds including those from cars, trains, mining machinery and aircraft (Pijanowski et al., 2011a), but also including speech and music. The term technophony is more specific, relating only to mechanical sounds (Farina, Buscaino, Ceraulo & Pieretti, 2014a).

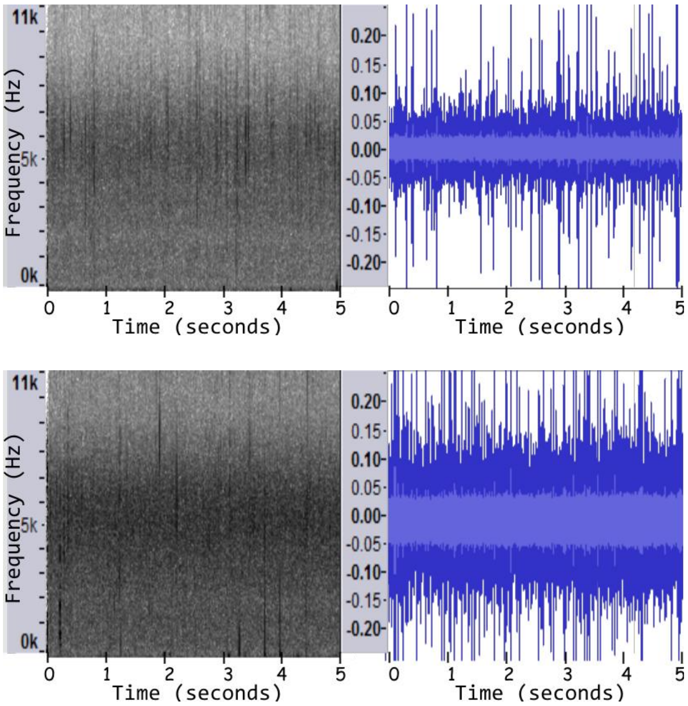


Figure 2.4 The spectrogram and corresponding waveform of five seconds of light to moderate rain (top) and heavy rain (bottom). The waveforms to the right indicates a higher rate of sound events. These images were generated in Audacity (Ash et al., 2017).

The word *soundscape* and other terms such as *soundmark* and *keynote sounds* have come from Schafer (1994). These terms relate to the concepts of landscape and of place. Keynote sounds set the scene, reminding us of where we are (Schafer, 1994, p.12 & 152). Whereas, *soundmarks* are sounds that help define a community, for example the sound of a town's bell (Schafer, 1994, p.10). These terms have more relevance in the context of urban rather than natural soundscapes.

A Soundscape Ecology model (refer to Figure 2.5) (Pijanowski et al., 2011a) identifies four components contributing to the patterns in *Soundscape*. *The Human System* (A), regulated by rules, values and policies, creates the *Built Environment* (B), which produces human-made spatial and temporal sounds. *Landforms and Atmosphere* (C) interact to produce local climate regimes and associated geophony. This in turn affects the animals supported by the *Natural Environment* (D) altering the seasonal patterns of biophony. Collectively all sounds produce the *Soundscape* (E). Habitat alteration caused by the Human System affects the Natural Environment and the Soundscape, which in turn feeds back to the Human System through what we hear and record (Pijanowski et al., 2011a). Perhaps another arrow should be used to indicate human-driven alteration of the atmosphere and hence the soundscape. Pijanowski et al. (2011b) have called for the development of automated methods to classify sounds into the three soundscape components, that is biophony, geophony and anthropophony.

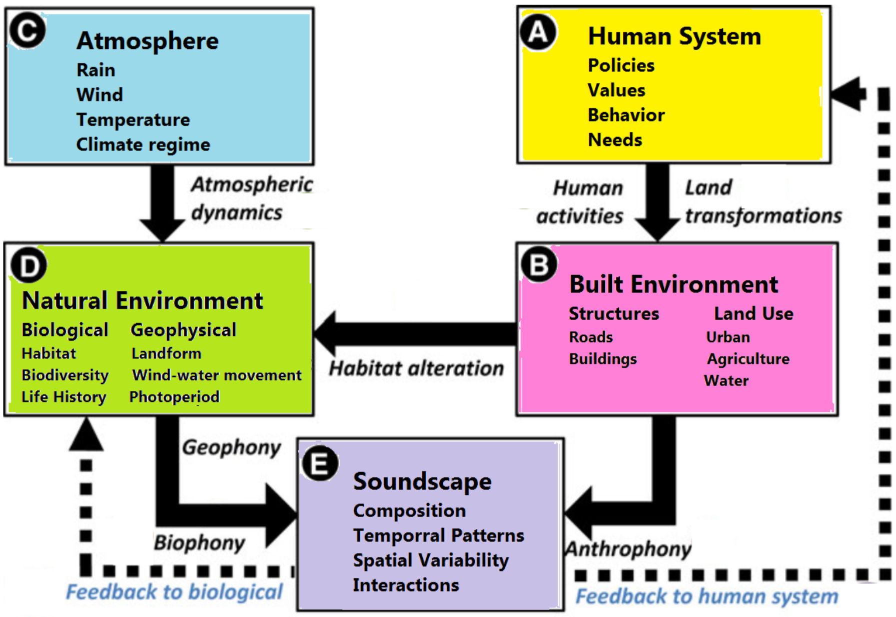


Figure 2.5 Conceptual Framework for Soundscape Ecology. Adapted from source: Pijanowski et al. (2011a).

Ecoacoustics has a specific ecological focus, using environmental sound to assess biodiversity and ecological processes across large spatial and temporal scales (Sueur & Farina, 2015). It incorporates many disciplines including the electronic, biological, computer, and social sciences. Acoustic indices are an important tool for the analysis of acoustic recordings (Sueur, Farina, Gasc, Pieretti & Pavoine, 2014) but other techniques which treat the spectrogram as an image have shown potential in quantifying bird communities in environmental recordings (Potamitis, 2014). However, most concentration has been placed on the identification of bird species and little effort has been put into the identification of the many insect species. Although, some research has focused on the automatic classification of insect species, for example (Ganchev et al., 2007; Riede, 1998).

2.3.1 Ecological Acoustic Hypotheses

The Acoustic Adaptation Hypothesis (Morton, 1975; Richards & Wiley, 1980) and the Acoustic Niche Hypothesis (Krause, 1992) are the main hypotheses that attempt to describe how animal vocalisations are shaped by the physical and sonic environments. The Acoustic Habitat Hypothesis (Mullet, Farina & Gage, 2017a) proposes that environmental sounds are used by animals to assess the suitability of the environment.

The Acoustic Adaptation Hypothesis (Hansen, 1979; Morton, 1975) proposes that the features of calls have evolved in response to the characteristics of habitats to maximise transmission and reduce degradation. Low frequency whistles suffer less degradation in closed forests compared to trilled calls and the reverse is true for open habitats (Brown & Handford, 2000; Morton, 1975; Richards & Wiley, 1980). Blumstein and Turner (2005) found higher frequency calls and harmonic calls were advantageous in open habitats in Australia. Boncoraglio and Saino (2007) found birds calling in closed habitats tend to have lower frequencies and a narrower frequency band in support of the Acoustic Adaptation Hypothesis.

The Acoustic Niche Hypothesis (Krause, 1992) proposes the 'acoustic space' is a finite resource where different frequency channels can be utilised by animals at the same or different times. Acoustic communities in undisturbed landscapes are thought to partition into different frequencies or times to limit inter-species interference (Krause, 1993).

The Acoustic Habitat Hypothesis (Mullet et al., 2017a) proposes that animals dependant on sounds occupy habitats that meet their need to communicate acoustically. "Sound-dependent species" are ones that rely on sounds produced by themselves and/or others animals and sounds from the natural environment to survive (Mullet et al., 2017a).

2.3.2 The Identification and Treatment of Noise

Noise associated with wind, rain, aircraft and/or cicadas is often removed prior to analysis (Buxton, Brown, Sharman, Gabriele & McKenna, 2016; Depraetere et al., 2012; Farina & Pieretti, 2014; Gasc et al., 2013b; Guyot et al., 2016; Leach, 2016; Rankin & Axel, 2017; Rodriguez et al., 2014; Sueur et al., 2008) or filtered out during analysis (Gasc et al., 2017; Pieretti et al., 2015). Calls from species other than a target species are often considered noise (Bardeli et al., 2010; Ulloa et al., 2016). However, others retain the sounds containing wind and rain, considering the ecological significance of these audio segments (Towsey et al., 2014b).

Noise pollution affects the ability of animals to sense predators, find food, and reproduce (Chan, Giraldo-Perez, Smith & Blumstein, 2010; Thorne & Shepherd, 2013). National parks are affected by noise pollution even in remote parts due to the exposure to noise from airplanes (Lynch, Joyce & Fristrup, 2011) and snowmobiles (Mullet, Morton, Gage & Huettmann, 2017b). Most anthropogenic noise occurs at low frequencies (Figure 2.6) and has the potential to mask low frequency bird calls (Slabbekoorn & Ripmeester, 2008).

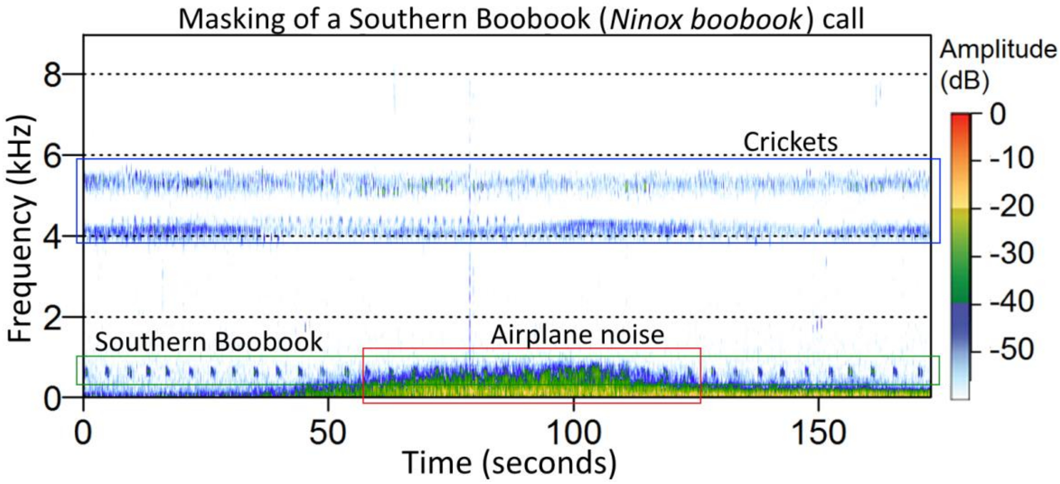


Figure 2.6 Masking of Southern Boobook (*Ninox boobook*) call by an aircraft, recorded at 3 am on the 18 March 2015 in Woondum National Park. The spectrogram was produced using R Seewave package (Sueur, 2014).

Geophonies can also mask animal calls (Pijanowski et al., 2011b). Climate change is predicted to change the patterns and intensity of geophony which could have implications for animal communication (Pijanowski et al., 2011a) and audio recording.

2.4 PROTOCOLS FOR THE COLLECTION OF AUDIO-RECORDINGS

The collection of acoustic data requires choices about the methods recording, collection, and storage. These include the choice of acoustic recorder, sampling rate, file format and bit-rate, microphone type (Blumstein et al., 2011; Obrist et al., 2010), recording schedule, and data storage and data accessibility. Some researchers have expressed the need to develop protocols for the collection of audio recordings and analysis of audio recordings (Pieretti et al., 2015). Following is a brief summary of each of the above choices.

2.4.1 Acoustic Recorders

The hardware for recording environmental sound, include field-ready recorders (ARBIMON/Sieve Analytics, 2018; Frontier Labs, 2018; Lunilettronik, 2016; Wildlife Acoustics, 2013), AudioMoth (Hill et al., 2018), and Raspberry Pi (Whytock & Christie, 2016). The recorder generally defines the microphone type, omnidirectional microphones being standard on most field-ready recorders (Wildlife Acoustics, 2013).

Following the development of autonomous recorders (Agranat, 2010), personnel were no longer needed to start and stop recordings (Sueur, Gasc, Grandcolas & Pavoine, 2012). Autonomous recorders have led to an increase in the volume of recordings, a greater spatial coverage, and targeted recordings of the dawn chorus (Farina et al., 2015; Kasten, McKinley & Gage, 2010). The Soundscape Explorer (SE(T)), records and processes sound files in real time into acoustic indices (Farina, 2018; Lunilettronik, 2016).

The AudioMoth can be programmed to target specific sounds, saving costs in battery use and card storage. These recorders are small, inexpensive and have a low-power requirement allowing a larger number to be deployed across larger spatial and temporal scales.

2.4.2 Sampling Rate

A survey of 38 journal papers containing the word/phrases “soundscape” and “sampling rate” was made. These papers included the themes of soundscape patterns, automatic call recognition, and acoustic behavioural studies. The survey indicated the sampling rate most commonly used was either 44.1 or 48 kHz, in 63% of papers. As most bird, amphibian and mammal calls and many insect call are in the lower frequency range of human hearing (Napoletano, 2004 p.48; Qi, Gage, Joo, Napoletano & Biswas, 2007 p.202) a sampling rate of 22.05 kHz is suitable. When making continuous recordings a lower sampling rate also enables significant savings in data storage.

2.4.3 Recorder Scheduling

The survey of the 38 journal papers also revealed that recordings are either made continuously or in equally spaced intervals throughout the 24-hour period, or a shorter period. A small number of studies combined these two methods. For example Eldridge, Casey, Moscoso and Peck (2016) recorded a multiple of half-hour blocks during the dawn chorus, midday and at dusk in addition to 3 minutes in 15 minutes during the rest of the day. Thirty-one percent used continuous uninterrupted recording of length at least 6 hours within a 24-hour period. Eighteen papers used equally spaced intervals. The 1 in 10 minute intervals was most common and was used in five papers. The 1 in 30 minute intervals was used in two papers. The remaining eight papers used alternative schedules or continuous recordings of less than 6 hours, each one different.

The question of whether to record continuously or in scheduled intervals has been addressed in a number of papers (Colbert et al., 2015; Gage, Wimmer, Tarrant & Grace, 2017b; Pieretti et al., 2015). Colbert et al. (2015) investigated the calls of the Wild Turkey (*Meleagris gallopavo spp.*) using two separate datasets, one recorded continuously and the other using a schedule of 10 minutes in 30 minutes throughout the day. Their results indicated very little difference between the conclusions drawn from either dataset. Gage et al. (2017b) calculated six acoustic indices on a two-month recording at intervals of one-minute and 30-minutes, comparing the mean and standard deviation of each. The results indicated there was no statistical difference between the average values sampled at either interval. Pieretti et al. (2015) tested five schedule intervals (5, 10, 20, 30 and 60 minutes) recording 1 minute in each of these. The schedules of 1 minute in 5 minutes and 1 minute in 10 minutes provided the most reliable estimates of the soundscape, although it may be dependent on the season (Pieretti et al., 2015). Scheduled intervals provide considerable savings to data storage space and battery life (Pieretti et al., 2015) and also on the time required for maintaining batteries and SD cards.

2.4.4 Data Accessibility

Campos-Cerqueira and Aide (2016) liken audio recordings to "museum specimens" arguing they can be re-examined at any time in the future assuming the data has been stored and maintained. A similar statement covering all scientific data has been expressed by Hampton et al. (2013). Some scientific journals require data to be made publicly available. Storage and access to data needs consideration at the time of collection.

2.5 DATA REDUCTION IN ACOUSTICS

The complexity of acoustic data is recognised as a challenging aspect of its analysis (Bardeli et al., 2010; Kasten et al., 2012). The complexity of unsupervised very-long-duration environmental acoustic data requires data reduction before it becomes interpretable. Data reduction involves the grouping or summarising of data which often involves visualisation (Friel et al., 1997). Effective data reduction produces a reduced dataset with little loss of information (Çiflikli & Kahya-Özyirmidokuz, 2010). The data reduction techniques currently used with acoustic data are summarised below; these are acoustic indices and clustering.

2.5.1 Acoustic Indices

More than twenty acoustic indices have been developed since 2009 (Sueur et al., 2014). Acoustic indices provide numerical summaries of some aspect of the distribution of acoustic energy in acoustic recordings. The evaluation of the effectiveness of the acoustic indices in providing measures of species abundance and diversity has been investigated by a number of researchers (Ferreira et al., 2018; Gage et al., 2017b; Gasc et al., 2013a; Gasc et al., 2013b; Mammides, Goodale, Dayananda, Kang & Chen, 2017; Sueur et al., 2008). Acoustic indices can either be alpha or beta diversity indices. Alpha diversity indices estimate diversity within a community and beta diversity indices compare between communities (Sueur et al., 2014). The review that follows aims to outline the breadth of the acoustic indices in use.

Acoustic Complexity Index (ACI)

The Acoustic Complexity Index (ACI) (Pieretti et al., 2011) measures "the variability of the intensities registered in spectrograms" (Farina et al., 2014b). ACI was designed to measure "the relative difference between two consecutive intensity values along a selected frequency band" (Farina, Pieretti & Malavasi, 2014c). A short-time Fourier transform (STFT) is used to supply a matrix of intensities required to derive this index. To calculate the Acoustic Complexity Index, find ACI_f, the value for each frequency bin (Equation 1) and then find the sum of values in all frequency bins (Equation 2). ACI_f is found by calculating the sum of the differences between the amplitude in consecutive matrix frames $A_{k,f}$ and dividing by the total sum of the sound intensity in all frames within each frequency bin. In Equation 1, *f* is a single frequency bin, k is the frame index, and *n* is the number of frames. Dividing by the sum of intensities normalises for the effect of animal calls close to the microphone (Pieretti et al., 2011). ACI is then calculated by finding the sum of the ACI_f values using Equation 2, were N is the number of frequency bins (Pieretti et al., 2011).

$$ACI_f = \frac{\sum_{k=1}^{n-1} |A_{k,f} - A_{k,f+1}|}{\sum_{k=1}^{n-1} A_{k,f}} \quad (1)$$

(Pieretti et al., 2011)

$$ACI = \sum_{f=1}^{N} ACI_f \quad (2)$$

(Pieretti et al., 2011)

As this index was designed to detect complex animal sounds, it filters out monotonous human-made sounds (anthropophony) such as car and aircraft noise because these do not have rapid changes in intensity over short time periods (Farina, Pieretti & Piccioli, 2011). Gusty wind increases the index (Farina et al., 2011; Towsey, Wimmer, Williamson & Roe, 2014a). The dawn chorus also increases the ACI index and night-time recordings have low values of ACI because of low amplitude variations throughout the night, but increases occur when nocturnal birds are calling (Towsey et al., 2014a). An additional ACI indices were introduced and used in the Ecoacoustics Event Detection and Identification (EEDI) (Farina, Gage & Salutari, 2018; Farina & Salutari, 2016) method.

Acoustic Entropy Index H, H_f and H_t

The acoustic entropy index (H) was adapted for use in acoustics from the Shannon diversity index in Ecology (Sueur et al., 2008). In a simulated bird assemblage test, this index increased with the number of vocal species present (Sueur et al., 2008). However, erroneous estimates were achieved when this index was tested in recordings containing sounds from aircraft, cars or trains (Depraetere et al., 2012).

The acoustic entropy index, H, is derived from the product of the temporal entropy H_t and the spectral entropy H_f, ($H = H_t \times H_f$) (Sueur et al., 2008). The index H is designed to approximate 0 for pure tones and 1 for random noise (Sueur et al., 2008). Acoustic entropy (H) is an *alpha diversity* measure, that is it measures the acoustic diversity within communities (Depraetere et al., 2012; Sueur et al., 2008). Temporal entropy H_t is derived from the probability mass function of the wave envelope, pmf(t) using Equation 3, where n is the number of frames (Depraetere et al., 2012; Sueur et al., 2008). Spectral entropy H_f is derived using Equation 4 from the probability mass function of the mean spectrum, pmf(f) (from the STFT), where N is the number of frequency bins (Depraetere et al., 2012; Sueur et al., 2008).

$$H_t = -\sum_{t=1}^{n} pmf(t) \times \frac{log_2(pmf(t))}{log_2(n)} \quad (3)$$ (Sueur et al., 2008)

$$H_f = -\sum_{f=1}^{N} pmf(f) \times \frac{log_2(pmf(f))}{log_2(N)} \quad (4)$$ (Sueur et al., 2008)

Bioacoustic Index (BIO)

The Bioacoustic Index (Boelman, Asner, Hart & Martin, 2007) calculates the area under the power spectrum, typically between 2 and 8 kHz. When applied over eight minute recordings at eight independent sites in Hawaii it was highly correlated with bird-count data (Boelman et al., 2007).

Normalised Difference Soundscape Index (NDSI)

The Normalised Difference Soundscape Index (NDSI) (Kasten et al., 2012), as the name suggests, is a normalised comparison between two soundscape components, biophony and anthropophony. In Equation 5; α and β are the power spectral density (PSD) of the sounds in the range 1-2 kHz (human-made) and 2-11 kHz (natural sounds). However, not all sounds below 2 kHz are human-made, and not all biophony is above 2 kHz (see Figures 2.1, 2.3 and 2.6). Researchers have lowered the 2 kHz threshold 300 Hz to better reflect the biophony in their data (Ferreira et al., 2018). The index ranges from -1 (all anthropophony) to +1 (all biophony).

$$NDSI = \frac{\beta - \alpha}{\beta + \alpha} \quad (5)$$ (Kasten et al., 2012)

Acoustic Evenness Index (AEI)

The Acoustic Evenness Index (AEI) (Villanueva-Rivera et al., 2011) based on the Gini index measures the evenness of the frequency distribution. A distribution with uniform acoustic energy across all frequency bins will have a value of 0. Distributions with all acoustic energy in one frequency bin will have a value of 1.

Acoustic Dissimilarity Index (D)

The dissimilarity index (D) gives an estimate of the compositional diversity between communities (Depraetere et al., 2012; Gasc et al., 2013b). Dissimilarity indices decrease with an increase in the number of common species; in bioacoustics, this is the number of common vocalising species at two locations (Gasc et al., 2013a; Sueur et al., 2008).

The dissimilarity index (D), an extension of the compositional dissimilarity measure (Faith, Minchin & Belbin, 1987), has two sub-indices, the temporal dissimilarity index D_t and the spectral dissimilarity index D_f, these are multiplied to give the dissimilarity index, $(D = D_t \times D_f)$ (Depraetere et al., 2012; Sueur et al., 2008). The temporal dissimilarity index, D_t is derived using Equation 6 from the difference between the probability mass function of the amplitude envelopes of each sound, $pmf_1(t)$ and $pmf_2(t)$, where n is the number of frames and t is the frame index (Depraetere et al., 2012; Sueur et al., 2008). Spectral dissimilarity index, D_f is derived using Equation 7 from the difference between the probability mass function of the mean spectrum of each sound, $pmf_1(f)$ and $pmf_2(f)$, where N is the number of frequency bins and f is the frequency bin index (Depraetere et al., 2012; Sueur et al., 2008).

$$D_t = 0.5 \times \sum_{t=1}^{n} |pmf_1(t) - pmf_2(t)| \quad (6)$$ (Sueur et al., 2008)

$$D_f = 0.5 \times \sum_{f=1}^{N} |pmf_1(f) - pmf_2(f)| \quad (7)$$ (Sueur et al., 2008)

At a site in Tanzania, the dissimilarity index increased before sunrise and during warm sunny days, and decreased just after sunset (Depraetere et al., 2012), signifying a decrease in the number of common vocal species across sites in the morning and the opposite at sunset.

Sueur (2018b p.494-505) demonstrates the difference between D and other dissimilarity indices, including the Cumulative Frequency Dissimilarity Index (Lellouch, Pavoine, Jiguet, Glotin & Sueur, 2014).

Acoustic Indices in General

Studies have been conducted to determine the efficacy and consistency of the acoustic indices in assessing biodiversity (Fairbrass et al., 2017; Ferreira et al., 2018; Fuller, Axel, Tucker & Gage, 2015; Mammides et al., 2017). A critique by Eldridge et al. (2016) argued that current acoustic indices are ineffectual because they extract information from either the time or frequency domains rather than preserving the time-frequency structure.

Table 2.1 summarises the findings of six studies conducted in natural environments. From this table there appears to be an inconsistency of performance of each acoustic index. This may be partly due to the recording and analysis protocols used, but the extent of these differences was unexpected. What must be considered is that all of these indices can respond to sound sources other than biophony and therefore do not only measure species diversity (Sueur et al., 2012, p.108). Also entropy (H) is correlated logarithmically not linearly with species richness (Sueur et al., 2008).

Table 2.1: A summary of the correlations between acoustic indices and the measures of biodiversity.

Researchers, country, (number of sites) and taxonomic groups.	**Acoustic Complexity Index (ACI)**	**Temporal Entropy (H_t)**	**Biodiversity Index (BIO)**	**Normalised Difference Soundscape Index (NDSI)**	**Acoustic Evenness Index (AEI)**
Gage et al. (2017b), Australia (1), Taxa: Birds	Highly correlated with number of calls.	Correlated with the number of calls and species richness	Non-significant negative correlation with species richness	Non-significant positive correlation with number of calls	Correlated with calls and species richness
Fuller et al. (2015) Australia (19) Taxa: Birds and insects	Not sensitive to night-time insects. Demonstrate diurnal pattern of birds.	Correlation with species richness. High night-time values may relate to insects.	Demonstrate diurnal pattern of birds.	Correlation with species richness.	Good indicator of biocondition.
Mammides et al. (2017). China (multiple sites). Taxa: Birds	Negligible correlation with bird species richness and bird diversity during the dry and wet season.	Non-significant positive correlation with bird species and bird diversity during the dry and wet season.	Low positive correlation with bird species and bird diversity during the dry season.	Low to moderate positive non-significant correlation with bird species and bird diversity during the dry season.	Non-significant negative correlation with species richness.
Ferreira et al. (2018).Brazil (3) Taxa: Amphibians and birds	Moderate correlation with anurans at one site. Low or negative correlation with birds and insects.	Correlations with anurans at all three sites and insects at one site. Negative correlation with birds at two sites.	Inconsistent, correlated with anurans and insects at one site but negative or negligible correlation at the other two sites.	Negative correlation with birds. High correlation with insects and anurans at one site.	Negative correlation with anurans at three sites.
Ross et al. (2018). Japan (5). Taxa: Birds, amphibians and insects	Increased with rainfall, orthoptera and cicada calls.	Not in this study.	Peak at dawn. Decreased by wind. High at night due to orthoptera.	Highest in forest site. High during dawn bird and evening amphibian chorus.	Increased by wind.
Retamosa Izaguirre, Ramírez-Alán and De la O Castro (2018) Costa Rica (12). Taxa: Birds	Positive correlation with bird abundance, negative correlation with species richness.	Not in this study	Peaks during dawn and dusk. Negative correlation with bird diversity.	Related to the number of trees.	Moderate correlation with bird abundance.

Ecoacoustic Analysis

Acoustic indices are an important means of soundscape analysis (Sueur et al., 2014). These have been applied to measure biodiversity (Gasc et al., 2015; Pekin, Jung, Villanueva-Rivera, Pijanowski & Ahumada, 2012; Sueur et al., 2014), ecosystem viability (Tucker et al., 2014), beta (community) diversity (Depraetere et al., 2012; Sueur et al., 2008) and the phenology of migrating birds (Buxton et al., 2016).

Some acoustic indices produce an unexpected result under certain conditions (Depraetere et al., 2012; Gasc et al., 2015) however this can be used to filter unwanted sounds (Rankin & Axel, 2017, p.134). For example, the Acoustic Complexity Index (ACI) increases with rain, wind and machine noises (Depraetere et al., 2012) and the acoustic entropy index gave erroneous estimates due to the sound of aircraft, cars and trains (Depraetere et al., 2012).

Acoustic indices are also used in acoustic visualisation (Towsey et al., 2014b). Visualisation opens up many possibilities for the interpretation of the contents of long-duration audio recordings.

2.5.2 Clustering

Previous studies have used clustering to classify soundscapes (Bormpoudakis, Sueur & Pantis, 2013; De Coensel, Botteldooren, Debacq, Nilsson & Berglund, 2008; Rychtáriková & Vermeir, 2013; Sankupellay, Towsey, Truskinger & Roe, 2015; Torija, Ruiz & Ramos-Ridao, 2013; Yang & Kang, 2013). Most of these were applied to urban soundscapes. Two studies (Bormpoudakis et al., 2013; Sankupellay et al., 2015) related directly to natural environmental recordings, and none related to continuous or long-duration recordings. Clustering has not been previously used to interpret long-duration natural environmental recordings.

De Coensel et al. (2008) and De Coensel, Botteldooren, Debacq, Nilsson and Berglund (2007) used fuzzy ant clustering (Deneubourg et al., 1991), a method conceptually based on the social behaviour of ants. The acoustic features used included one-third octave band frequency values, sound pressure levels (SPL) and temporal measurements determined from 1116 soundscapes recorded at 16 parks in Stockholm (De Coensel et al., 2007). The fuzzy ant clustering algorithm is stopped when the ‘fitness’ between iterations stabilises indicating the convergence of the clustering algorithm (De Coensel et al., 2008). The clustering did not converge so the clustering with the greatest ‘fitness’ was selected, this produced 49 clusters (De Coensel et al., 2008). Cluster validation involved the use of a questionnaire performed on randomly selected people during the recordings (De Coensel et al., 2008). The clustering revealed some of the perceived variation in the soundscapes as detected by the questionnaire (De Coensel et al., 2008). The failure of this clustering method to converge raises some concerns and will therefore not be considered for the larger acoustic dataset analysed in this thesis.

Rychtáriková and Vermeir (2013) recorded 370 "soundwalks" lasting 15-20 minutes, which were analysed to extract thirteen acoustic features. The acoustic features included measures of sound pressure levels, temporal, frequency and spatial information (Rychtáriková & Vermeir, 2013). The hierarchical clustering producing 20 clusters which aligned with the subjective expectation of the type of location for example a busy road, side street, park, or residential area (Rychtáriková & Vermeir, 2013).

Torija et al. (2013) used 49 acoustic measurements mostly consisting of sound-pressure-level readings in addition to qualitative descriptors to hierarchically cluster the soundscapes of 54 locations. As with the study of De Coensel et al. (2008), people passing by were used to provide perceptual interpretation of the soundscape (Torija et al., 2013). Correlations were established between acoustic measurements and the subjective descriptors (Torija et al., 2013).

Yang and Kang (2013) clustered the acoustic features extracted from 101 audio recordings (duration 30-seconds) using hierarchical clustering. The acoustic features used included loudness, roughness, tonality and sharpness in addition to others and the statistical average and limits of each (Yang & Kang, 2013).

In contrast to the studies mentioned above, Bormpoudakis et al. (2013) used self-organising maps and an ensemble classifier, Random-forest, to determine the importance of acoustic features in distinguishing between the ambient sounds from different habitats in Northern Greece. They used 10-second segments from 32 sites to distinguish habitats and between forests and forest edges. The differences were due to the tree density, leaf morphology, leaf litter and the presence of birds and/or insects. All recordings were made during September 2010 and no further research was completed to indicate the results in other seasons.

Sankupellay et al. (2015) also used self-organising maps, this time to cluster a twelve-day, nine-dimensional (nine acoustic indices) dataset, consisting of recordings from two days from six sites in Southeast Queensland. Twenty-four hour acoustic signatures were used to compare the soundscape of two similarly structured ecosystems. An *acoustic signature* (Sankupellay et al., 2015) is a frequency histogram of the count of the number of each cluster within a 24-hour period. They established that the soundscapes of consecutive days at the same site were more similar than those of days more separated in space.

Following is a brief outline of the main clustering techniques used in this thesis, partitional, hierarchical, model-based and hybrid methods.

Partitional Clustering

K-means is the most broadly used partitional clustering algorithm (Wu et al., 2008). The k-means algorithm (Hartigan & Wong, 1979) starts with an initialisation of a set of *k* cluster centres, and all observations are immediately assigned to the nearest cluster centre (Wu et al., 2008). The mean of each cluster is calculated and these become the new centres or centroids (Hartigan & Wong, 1979). All observations are re-assigned to the nearest of the centroids requiring N×k evaluations, where N is the number of observations and k is the number of clusters (Wu et al., 2008). The iterations continue until the algorithm converges, when no further movement of observations occurs amongst the clusters (Wu et al., 2008).

The initial partitions are often selected at random from rows in the dataset, unless a seed has been set. K-means is fast, easy and efficiently performed and is suitable for large datasets (Wu et al., 2008). The disadvantages are: 1. the initial partitions are randomly selected, 2. the k value needs to be specified in advance and 3. the clustering is sensitive to the initial partitions (Saitta, Raphael & Smith, 2007; Wu et al., 2008).

Hierarchical Clustering

Agglomerative hierarchical clustering commences with the number of singleton clusters equal to the number of observations, N. The method proceeds by iteratively merging the two most similar observations based on the criteria of the method selected (for example, *Ward* or *average*). Cluster distances are recalculated before the merge of the next nearest observations. This process continues for N-1 steps until all observations are merged. The structure of the hierarchical clustering is displayed as a dendrogram (Murtagh & Legendre, 2014).

Two clustering methods are discussed, the *average* and the *Ward* (1963) methods. The *average* method considers the size of two clusters I and J (n_I and n_J) and the distance, d, between the clusters and any other cluster K. Using the update distance formula (see F1 below), the clusters with the lowest 'distance' are merged (Lance & Williams, 1967; Müllner, 2013).

$$\begin{matrix} distance \\ updating \\ formula \end{matrix} \qquad \frac{n_I\, d(I,K) + n_J\, d(J,K)}{n_I + n_J} \qquad (F1)$$

(Lance & Williams, 1967; Müllner, 2013)

The *Ward* method, based on Ward's criteria (1963) uses a sum-of-squares distance updating formula (see F2 below), minimising the within-cluster dispersion (Müllner, 2013; Murtagh & Legendre, 2014). This method considers the cluster size of the two clusters I and J (n_I and n_J) and the distance, d, between the clusters and the size (n_K) of any other cluster K.

$$\begin{matrix} distance \\ updating \\ formula \end{matrix} \quad \sqrt{\frac{(n_I + n_K)d(I,K)^2 + (n_J + n_K)d(J,K)^2 - n_K\, d(I,J)^2}{n_I + n_J + n_K}} \quad (F2)$$

(Kaufman & Rousseeuw, 1990 , p.230-234; Müllner, 2013)

Model-based Clustering

Model-based clustering attempts to fit the observations to a statistical model (Andreopoulos, An, Wang & Schroeder, 2008). Unlike partitional clustering (k-means) which requires a selection of k before the algorithm proceeds, model-based clustering uses the Bayesian Information Criterion (BIC) to determine the optimum number of clusters (Fraley & Raftery, 2002).

The procedure begins with singleton clusters. Using model-based hierarchical clustering, clusters are merged in order to maximise the classification likelihood (Fraley, 1998). The BIC is penalised for the number of parameters allowing the comparison of different models. The maximum BIC predicts the optimum model (Fraley & Raftery, 2007). The memory requirement is equivalent to the square of the number of observations making model-based clustering slow (Andreopoulos et al., 2008; Fraley & Raftery, 2002).

Hybrid Clustering

Hybrid clustering consists of the pairing of two clustering algorithms. In this thesis for example, we paired k-means with hierarchical clustering. The advantages of one method can overcome the disadvantages of the other (Wu et al., 2008).

Clustering of Sound Events

Clustering is used in sound event classification to either produce states for hidden Markov models or to cluster acoustic features. Kaleidoscope (Wildlife Acoustics, 2017), detects audio events and calculates discrete cosine coefficients, these vectors are clustered to provide the initial states for hidden Markov models. A Hidden Markov model is a probabilistic model determined from a state sequence without knowledge of the process occurring to generate the sequence (Rabiner, 1989). Fisher scores are a measure used to determine the similarity between events (Wildlife Acoustics, 2017).

Potamitis (2014) used an image analysis technique to identify regions of interest and apply a mask to birdcalls. The 2-dimensional image of the birdcall is converted to a binary image that subsequently forms a mask of the region. Masks are produced for all species calls in the training set and test set. The region beneath the mask is considered and the features extracted from 16 equal horizontal bands form an 80-vector feature set for each call (Potamitis, 2014). Other features are also determined. The extracted features are clustered to enable the identification of species to an accuracy of 86%. The described method is not applicable to cicadas because of the noise-like nature of their calls (Potamitis, 2014). Similar techniques were also developed by Morfi and Stowell (2017).

2.6 ACOUSTIC VISUALISATION

Acoustic visualisation is evolving with the needs of the users of acoustic data. For decades, the cost of recording equipment and storage kept the amount of sound recorded low, by comparison to today. The grey-scale spectrogram (Potter, 1945), developed more than 70 years ago, met the needs of these short recordings. However, with the increasing volume of recordings, other methods of acoustic visualisation were required to facilitate longer recordings. This section outlines the main types of acoustic visualisation.

2.6.1 Grey-scale Spectrograms (Sonograms)

Spectrograms provide information that cannot be determined by listening alone due to limits in human hearing, as they provide precise information on frequency and structure (Riede, 1998). Spectrograms remain an essential tool in the review of audio recordings and they are routinely used for calculating acoustic indices (Sueur et al., 2014) and for call recognition (Brandes et al., 2006; Potamitis, 2014).

Grey-scale spectrograms are the result of the application of a Fast Fourier transform (FFT) on audio segments. The FFT decomposes the time series to a weighted sum of sine and cosine functions (Sueur, 2014). The number of sine functions calculated is dependent on the window length, which determines the frequency and time resolutions of the spectrogram. A window length of 512 produces 256 sine functions. Each sine function defines the amplitude of the frequency band. The sampling rate and window length determines the resolution in both frequency and time.

2.6.2 Long-Duration False-Colour (LDFC) Spectrograms

More recently Towsey et al. (2014b) developed LDFC spectrograms. These images visualise the soundscape over a twenty-four-hour period. This is achieved by mapping three near-orthogonal spectral acoustic indices to the red, green, and blue (RGB) channels of the image (Towsey et al., 2014b). They retain frequency information but not call structure. The vertical resolution remains the same as the FFT from which the spectral acoustic indices are calculated. The temporal (horizontal) resolution in a standard false-colour spectrogram is 60 seconds, matching the time across which the acoustic indices are routinely calculated. Along with major sound events such as rain and wind, it is possible to identify single species in LDFC spectrograms if one or more birds of the same species have called repeatedly over a period of usually more than one minute (Towsey et al., 2014b).

2.6.3 Other Methods of Visualisation of Long-duration Audio Recordings

Visualisation techniques suitable for long-duration audio recordings are limited. Soundscape maps developed by Pijanowski et al. (2011b, Figure 10) display variations in the acoustic complexity index across landscapes. However individual plots are required for each day. Ross et al. (2018, Figure 3) used spiral plots to display the absolute values of five acoustic indices. These plots display changes in the acoustic indices across 17 days showing the diel patterns in these indices. However, using this method on very long recordings of the length of months or years would require increasing space and it may not allow the navigation to a particular day. Gage and Axel (2014, Figures 8 and 10) and Gage et al. (2017b, Figure 3) developed contour plots to map the acoustic index values against 24-hour time and the days of the year within a specific frequency band calculated on one minute samples taken every 30 minutes. These plots show one aspect of the acoustic energy obtained from single acoustic indices across time. They do not however visualise the contents of the long-duration recordings in a way that can be interpreted outside of an understanding of the acoustic index used and the frequency band being displayed.

Using Event Detection and Identification (EEDI) (Farina & Salutari, 2016), Farina et al. (2018) visualised 240 minutes of data. The minutes were visualised by plotting the first two indices and colour-coding the third index. The visualisations distinguish the minutes containing geophonies from those containing biophonies.

2.7 ECOLOGICAL INTERPRETATION

Like other forms of environmental data, acoustic recordings are analysed to extract information, for various purposes, for example to determine the presence of particular species. The terms *ecological* (or *biological) information* are often used to explain what is obtained or desired from audio recordings (Eldridge et al., 2016; Gage, Towsey & Kasten, 2017a; Jahn, Ganchev, Marques & Schuchmann, 2017; Mullet, 2017; Napoletano, 2017; Towsey, Truskinger & Roe, 2015; Ulloa, Aubin, Llusia, Bouveyron & Sueur, 2018). Sueur and Farina (2015) use ecological information to define the scope of Ecoacoustics "*The use of sound as a material from which to infer ecological information enables ecoacoustics to investigate the ecology of populations, communities, and landscapes*". For this thesis, ecological information is defined as that which is inferred from an ecologically informed interpretation of acoustic indices, acoustic clusters, and visual representations of long-duration recordings of environmental soundscapes. This definition includes information that can be inferred from the patterns and cycles in the acoustic clusters. These inferences will enable the interpretation of the very-long-duration audio recording. The range of information that can be inferred from audio recordings is diverse. A brief discussion of this information is provided under the themes of biodiversity and ecological processes.

2.7.1 Biodiversity

Biodiversity guards against declines in ecosystem function by building in redundancy amongst the community of species (Yachi & Loreau, 1999). Methods to monitor threatened, endangered, cryptic, or secretive species are an important aspect of maintaining biodiversity. Laiolo, Vögeli, Serrano and Tella (2008) used song repertoire size and call rate to determine population viability of a threatened songbird. LDFC Spectrograms can be an efficient method to find secretive vocal or endangered species (Dema et al., 2017; Towsey et al., 2018b). Campos-Cerqueira and Aide (2016) used the output from a classifier built using RandomForest to build an occupancy model for a cryptic species. While the classifier produced a reasonably low rate of false-positives (23.9%), the detection of calls was low compared to manual detection.

2.7.2 Ecological Processes

The field of Ecoacoustics was brought about by the need to focus on the connection between sound and ecological processes (Farina, 2018). The loss or changes to ecological processes over time is linked to the extinction and endangerment of species (McQuillan et al., 2009). Ecological processes include the interaction between species, including keystone species, hydrological cycles, long-distance species migration, natural disturbance regimes, climatic changes, flows of nutrients, evolutionary processes including genetic diversity and the heterogeneity of landscapes (Bennett et al., 2009; McQuillan et al., 2009). The documentation of the phenology (the timing of cycles of plants and animals) is becoming increasingly important for monitoring changes due to climate (Rosemartin et al., 2014). This incorporates a study of ecological processes, for example bird migration in Alaska, see Buxton et al. (2016). Invasive species are one of the key contributors to ecosystem change (Novak, 2007), a number of studies have revealed ways of detecting invasive species using acoustics. For example the Cane Toads in Northern Territory, Australia (Grigg, Taylor, McCallum & Fletcher, 2006) or an invasive ant species (Gasc et al., 2017).

2.8 ANALYTICAL TECHNIQUES FOR ENVIRONMENTAL ACOUSTIC RECORDINGS

While manual labelling of acoustic recordings by experts is accurate, it is time-intensive (Bardeli, 2009; Kogan & Margoliash, 1998). Alternatively, automatic species recognition are usually limited to species-specific recognisers, frequently with high numbers of false-positives (Colbert et al., 2015; Jahn et al., 2017; Rocha, Ferreira, Paula, Rodrigues & Sousa-Lima, 2015).

2.8.1 Species Call Recognition

Accurate identification of bird and other animal vocalisations within acoustic recordings is difficult and is usually completed either by experienced birders (Figure 2.7), automatically, or in combination (Bardeli, 2009; Grigg et al., 2006; Tachibana, Oosugi & Okanoya, 2014; Tucker et al., 2014).

Automatic classification is best achieved with ‘clean’ or high SNR recordings (Kaewtip, Tan, Alwan & Taylor, 2013). Training algorithms require large numbers of recordings (Acevedo et al., 2009) and these datasets are hard to obtain (Bardeli, 2009; Priyadarshani, Marsland & Castro, 2018; Towsey et al., 2014b). Song birds with moderate to large sized repertoires (Ames, 1971, p.136; Beecher & Brenowitz, 2005) or regional differences (Acevedo et al., 2009; Brandes, 2008a) increase the complexity of classification.

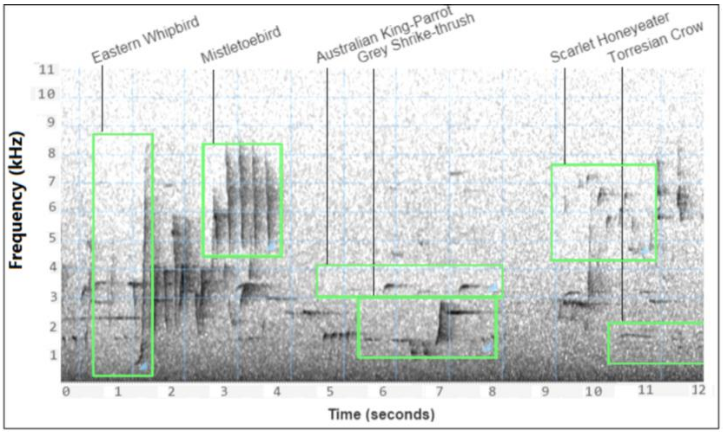


Figure 2.7 A grey-scale spectrogram showing manually labelled birdcalls (QUT Bioacoustics Workbench, 2016).

2.8.2 Image Processing Techniques

Template matching can be used to identify the calls of species if the calls remain reasonably consistent (Ulloa et al., 2016) but, this is often not the case. In this method, spectrograms in the training set are cross-correlated with the spectrograms in the dataset (Ulloa et al., 2016).

Many large databases of animal calls were originally collected to target the call of a particular species, and as a result the metadata of each recording often does not contain the list of other background species in each recording (Bardeli, 2009). Content-based retrieval (Bardeli, 2009), an image processing technique, uses structure tensors to facilitate the searching for birdcalls in recordings. Dong, Towsey, Zhang, Banks and Roe (2013) developed this further, using a technique to detect ridges in spectrograms. As these techniques are non-species-specific, they have the potential to be applied to a large number of species. Potamitis (2014) proposed another image-processing technique, which has been previously discussed.

2.8.3 Pattern Classification

Kasten et al. (2012) developed an unsupervised pattern classifier to classify biophonic sounds in long-duration audio recordings. The original signal, a time-sequence is data reduced by normalising and calculating the mean of equal length segments in the sequence. This reduced sequence is further reduced using Symbolic Aggregate approXimation (SAX) (Lin, Keogh, Lonardi & Chiu, 2003) to provide a series of letters or a “word”. These words were then grouped using hierarchical clustering. Labelled segments can then be used to identify similar sounds.

2.9 SUMMARY AND IMPLICATIONS

This literature review revealed that although the identification of acoustic events within recordings has received intensive efforts, the recognisers are not accurate enough to be relied on for automatic species richness. The use of automatic classification for census data and biodiversity assessment is therefore some years away. However, this work is ongoing and developments such as content-based retrieval (Dong et al., 2013) have the potential to improve this.

Acoustic indices are a promising tool used for the assessment of species richness and compositional diversity between sites. However, when used individually, acoustic indices can be inconsistent in the presence of rain, wind or anthropophony (Depraetere et al., 2012; Gasc et al., 2015). The implication for the application of single acoustic indices is that caution must be used in order to reduce incorrect conclusions due to the presence of sounds which confound these indices.

Previous clustering of soundscapes has used multiple acoustic features on mostly urban soundscapes using a limited number of sound samples. These have shown that clustering has the potential to provide meaningful clusters. Hierarchical clustering was used in the majority of these studies (see Section 2.5.2). This choice may have been due to the limited length of the recordings being analysed. However, it is not possible to apply hierarchical clustering to recordings of the length proposed in this study. It will therefore be necessary to investigate the clustering method that will be most suitable for large datasets.

Visualisation techniques suitable for interpreting short and long-duration recordings to the length of one day are available, but they do not extend to very-long-duration recordings. The implications for the lack of visualisation techniques for very-long duration recordings is the limitation of the ecological interpretation that can be made from these recordings.

No study before has attempted to use multiple acoustic indices to classify very-long-duration continuous audio data from a single site or multiple sites in a natural environmental setting. Neither has any study attempted to utilise the potential of multiple acoustic indices to cluster very-long-duration data from natural sites.

Chapter 3

Surveys of Recording Sites

The interpretation of sounds in an environment is best understood with an understanding of the landscape characteristics from which the sounds originate (Qi et al., 2007, p.207-208). Sounds are a consequence of the vocalising communities and geological and anthropological processes. Ecosystem processes in natural environments are reliant on the availability of resources; food and shelter largely determine the species found. The soundscape itself is a resource for many species (Mullet et al., 2017a). The climatic conditions and patterns of disturbance that occur will also likely contribute to the presence of vocalising communities. The arrival and departure of migrating bird species and the emergence from underground of the cicadas during summer also affect the soundscape.

The site surveys provided reveal differences between the sites in vegetation species, vegetation structure, bird species, geology, and rainfall. These differences clearly indicate two different ecosystems. Understanding the sites is essential for the interpretation of the soundscape in subsequent chapters.

3.1 OVERVIEW

This chapter provides information about the recording sites gathered through site visits, desktop analysis and listening to the audio recordings. The desktop review included a analysis of available vegetation maps. Site visits were conducted weekly to change both the batteries and SD cards and during these visits, ground truthing and field observations were made of the vegetation and wildlife present at the sites. The bird, mammal, and cicada species list were obtained mostly by listening to audio recordings by the author; this is provided in Appendix B.

3.2 SITE SELECTION

The Gympie National Park site was selected because it had been part of an earlier study (Tucker, 2016) and as part of this study a biocondition (Eyre et al., 2015) assessment had been completed. The Woondum National Park site was chosen because it was regionally close, so it was possible to visit on the same day for data collection. It is part of a large now protected site and it provided a contrast to the first site with differences in vegetation, geology, and weather patterns.

3.3 REGIONAL CONTEXT

Gympie and Woondum National Parks are large areas covering 1768 hectares (4369 acres) and 4001 hectares (9887 acres) respectively (Queensland Government, 2013a, 2013b) (see Figure 3.1). They were previously state forests (until 2002 and 2001 respectively) and forest reserves (until 2006 and 2009 respectively) (Queensland Government, 2013a, 2013b). These National Parks were gazetted in conjunction with the South-East Queensland Forests Agreement aimed at improving outcomes for conservation (McAlpine, Peterson & Norman, 2005). The sites are 25 kilometres apart and about 150 kilometres north of Brisbane, Queensland, Australia. Gympie National Park is north of the city of Gympie and further inland than Woondum National Park, which lies to the southeast (Figure 3.1). The site locations and regional contexts are provided in Table 3.1.

3.4 VEGETATIVE CONTEXT

3.4.1 The Gympie National Park Site Vegetation

The recording site within Gympie National Park has a predominance of Spotted Gum (*Corymbia citriodora subspecies variegata*) on metamorphosed sedimentary rock substrate (Queensland Herbarium, 2014, 2015). This main tree species provides food in the form of flowers, sap, seeds, manna, bark and leaves for animals (Queensland Museum, 2003 p.141). These animals include the Yellow-bellied Glider (*Petarus australis*) (Eyre & Goldingay, 2005), Greater Glider (*Petauroides Volans*), Common Brushtail Possum (*Trichosurus vulpecula)* (Wormington, Lamb, McCallum & Moloney, 2002), Koala (*Phascolarctos cinereus*), Yellow-tailed Black Cockatoo (*Calyptorhynchus funereus*), Scaly-breasted Lorikeet (*Trichoglossus chlorolepidotus*), Noisy Friarbird (*Philemon corniculatus),* and Pale-headed Rosella (*Platycercus adscitus*) (Queensland Museum, 2003 p.141). Each of these species is vocal. All except the two glider species have been found in the recordings of this site or have been recorded on a Uovision wildlife camera (Uovision Europe, 2014) installed at the site during January, March, April and July 2016 (see Appendix C). Other vegetative food resources at Gympie National Park include the Mistletoe species (see photo in Table 3.2) the berries are an essential food source for the Mistletoebird (*Dicaeum hirundinaceum*) (Pizzey, 2014, p.486).

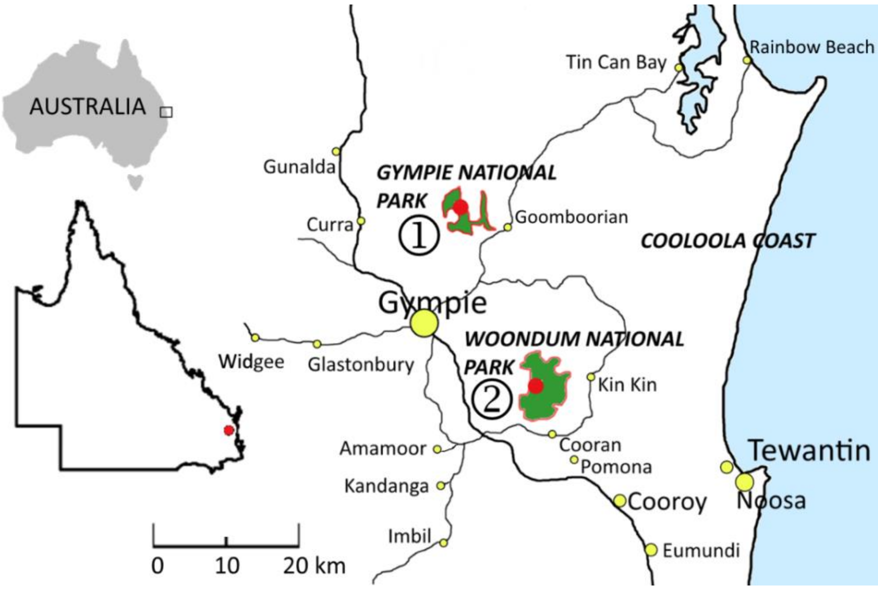


Figure 3.1 Location map of the recording sites (red dots) within the two national parks in Southeast Queensland. Site 1 in Gympie National Park and site 2 in Woondum National Park.

Table 3.1 Regional and Geographic Context of the Gympie and Woondum National Park sites

Description	**Gympie National Park**	**Woondum National Park**
Latitude	26° 3’ 49.6” South	26° 16’ 41.7” South
Longitude	152° 42’ 42.3” East	152° 47’ 51.4” East
Elevation	225 m	118 m
Inland distance	45 kilometres	28 kilometres
Slope	1:2.7 or 20.5°	1:5.5 or 10.4°
Aspect	North-North-West	North-West
Regional ecosystem (Queensland Herbarium, 2014, 2015)	12.11.5	12.12.15
Geology (Queensland Herbarium, 2014, 2015)	Metamorphosed sedimentary – shale	Igneous – granite

A recent fire (approximately 12 months before the recording started) had removed most of the groundcover (see photos in Table 3.2). Rain in June 2015 promoted new growth from underground lignotubers of the Spotted Gum *(Corymbia citriodora subspecies variegata)*. There is little groundcover apart from fallen leaves. During late spring and early summer (November to December 2015) the bark of the Spotted Gum and Grey Gum *(Eucalyptus propinqua)* sheds. Shedding bark is associated with the presence of arboreal marsupial mammals such as possums and gliders which forage for insects amongst the loose bark (Eyre & Buck, 2005). Groundcovers including the Blue Flax Lilly (*Dianella caerulea*) produce seeds and berries which attract fruit-eating birds including the Lewin’s Honeyeater (*Meliphaga lewinii*) (Queensland Museum, 2003 p.97).

3.4.2 The Woondum National Park Site Vegetation

The site within Woondum National Park has mostly Grey Gum (*E. propinqua*) and Pink Bloodwood (*Corymbia intermedia*) (Table 3.3) on igneous rock (Queensland Herbarium, 2014, 2015). These tree species provide food for a variety of animals including the Yellow-tailed Black Cockatoo (*Calyptorhynchus funereus*), Rainbow Lorikeet (*Glossopsitta pusilla*), Brown Cuckoo-dove (*Macropygia amboinensis*), Koala (*Phascolarctos cinereus*), Lewin's Honeyeater (*Meliphaga lewinii*), and Common Koel (*Eudynamys orientalis*) (Queensland Museum, 2003 p.144 & 236). Each of these species have been annotated in the recording (Appendix B).

Seasonal variability at the Woondum National Park site is more evident. The yearly growth cycle of Lantana (*Lantana camara*) includes flowering during winter before fruit formation and germination in spring. Lantana is a wide-spread non-native weed in Southeast Queensland (Queensland Government, 2013b). The fruiting and flowering species that provide food for birds include Lantana, Blue Flax Lilly (*Dianella caerulea*), Eucalypt species and the *Cissus Antartica*, a vine which fruits during autumn (Church, 1997; Queensland Museum, 2003 p.97, 144 & 161).

3.5 CLIMATIC CONTEXT

The nearest weather stations are at Gympie and Tewantin. Tewantin is 26 kilometres from the Woondum National Park site and the Gympie weather station is 15 kilometres and 16 kilometres from the Gympie and Woondum National Park sites respectively.

3.5.1 Temperature

The weekly site visits indicated, the Gympie National Park site has a broader temperature range compared to the Woondum National Park site. Figure 3.2 shows the average temperature range experienced at the Gympie and Tewantin weather stations nearby to the two sites. From the site visits, it was noted that the Gympie National Park site had higher average daytime temperatures during summer compared to the Woondum National Park site.

3.5.2 Rainfall

The difference in vegetation between the two recording sites (see Table 3.4) indicates a difference in rainfall and soil type. Gympie National Park site is classified as a dry eucalypt ecosystem whereas the Woondum National Park site is classified as wet eucalypt (Queensland Herbarium, 2014, 2015).

Table 3.2 Photos from Gympie National Park

 SM2+ recorder in situ	 Vegetation structure
 Tree canopy	 Mistletoe (*Dendrophthoe* species)
 Road access	 Groundcover
 Australian Magpie on wildlife camera	 Geology (Sedimentary) – shale

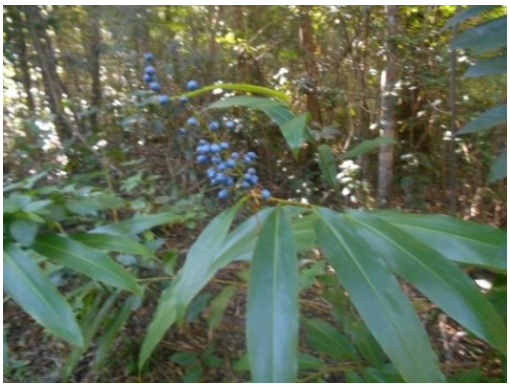
Photo credits: Yvonne F. Phillips [https://doi.org/10.4225/09/5a7ce77feb9e9].

Table 3.3 Photos from Woondum National Park

SM2+ recorder in situ


Vegetation structure


Tree canopy


Native Ginger (*Alpinia caerulea*)


No vehicle access permitted


Groundcover


Eastern Whipbird on wildlife camera


Geology (Igneous) - granite

Photo credits: Yvonne F. Phillips [https://doi.org/10.4225/09/5a7ce77feb9e9].

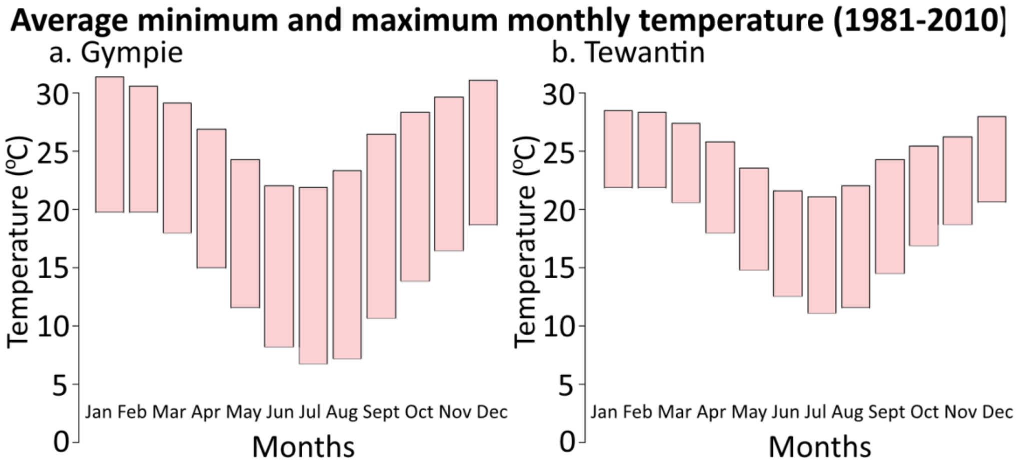


Figure 3.2 Average minimum and maximum monthly temperatures for a. Gympie and b. Tewantin for the years 1981 to 2010 (Australian Government Bureau of Meteorology, 2016a, 2016b). The site difference can be accounted for by the proximity to the coast.

3.6 SURVEYS OF VOCAL SPECIES

Species lists for the two National Parks indicate a general commonality between vocal species. The official species list for Gympie National Park has 71 birds, 13 mammals, 10 reptiles and 0 amphibians (Queensland Government, 2015a). The listing for Woondum National Park lists 119 birds, 28 mammals, 11 reptiles and 8 amphibians (Queensland Government, 2015b).

3.6.1 Birds

Of the 119 birds officially listed for Woondum National Park (Queensland Government, 2015b, 2015c), 53% are common to Gympie National Park. Woondum National Park has eight animal species of conservation significance; of these four are birds, Grey Goshawk (*Accipiter novaehollandiae*), Plumed Frogmouth (*Podargus ocellatus plumiferus*), Red-browed Treecreeper (*Climacteris erythrops*), and Sooty Owl (*Tyto tenebricosa*) (Queensland Government, 2013b). The latter two species were annotated in the recording from the Woondum National Park site (Appendix B) on the Ecosounds website (Truskinger et al., 2014). Annotation involves the placement of a bounding box around the call on the grey-scale spectrogram and placing a tag containing the species name.

Six bird species at Woondum National Park are listed in International Migratory Agreements with Japan, China and Korea, including the Black-faced Monarch (*Monarcha melanopsis*), Cicadabird (*Coracina tenuirostris*), Rufous Fantail (*Rhipidura rufifrons*), White-throated Needletail (*Hirundapus caudacutus*), Spectacled Monarch (*Symposiarchus trivirgatus*), and the Rainbow Bee-eater (*Merops ornatus*) (Queensland Government, 2013b).

Five out of six of these species were annotated in the recording (Appendix B). A similar survey of internationally significant birds is not currently available for the Gympie National Park site.

Table 3.4 Vegetative Character

Vegetation structure	Gympie National Park	Woondum National Park
Tree canopy	Spotted Gum (*C. citriodora subspecies variegata)* and Grey Gum *(E. propinqua).* Canopy height (30–35 metres). Mistletoe (*Dendrophthoe* species) grows in the tree canopy and flowers during September 2015.	Grey Gum (*E. propinqua*) and Pink Bloodwood (*C. intermedia*). Canopy height (30-35 metres).
Understorey	Sparse, same species as canopy. Acacia species within 200 metres of the recorder.	Lantana (*Lantana camara)*, a fruiting vine *Cissus Antarctica* grows nearby which both fruit from April to June 2016.
Ground layer	Grass including Molasses grass (*Melinis minutiflora)* and species including Blue Flax Lilly (*Dianella caerulea)* which fruits in December. Recently burnt (est. 2014) – very little vegetative ground cover apart some grass spp. and *dianella spp.* covering < 10% of the ground.	Ground layer – grass species and Basket Fern (*Drynaria rigidula*), epiphytes including Bird's Nest Fern (*Asplenium australasicum*), Native Ginger (*Alpinia caerulea)* and the Blue Flax Lilly (*Dianella caerulea).*
Leaf litter	Leaf and bark litter covers approximately 50% of the ground, changing throughout the seasons. Bark litters the ground in summer after the Spotted Gum sheds its bark.	Grass species cover < 10% and fallen leaf litter > 70% of ground. Many small diameter logs (< 0.2 metres) from fallen trees, granite rocks. The dry leaf litter made walking through the area audible.

Bird species were annotated in the recording by the author and later verified by an experienced local birder (Appendix B). Additionally, the Emerald Dove (*Chalcophaps indica*) was seen on the wildlife camera (Appendix C). The Willie Wagtail (*Rhipidura leucophrys*) and a flock of Topknot Pigeons (*Lopholaimus antarcticus*) were also sighted at the Gympie National Park site.

3.6.2 Amphibians

There are no amphibians listed for Gympie National Park (Queensland Government, 2015c). Woondum National Park has eight amphibians including the vulnerable Tusked Frog

(*Adelotus brevis)* and Cascade Treefrog (*Litoria pearsoniana)*. Neither of these frogs was annotated. However, the call of the Dainty green Treefrog (*Litoria gracilenta*) was recorded and annotated in the Woondum National Park recording. The calls of this species proceeded a storm, a known habit in certain frog species (Oseen & Wassersug, 2002).

3.6.3 Mammals

The Gympie National Park supports rodent species including Rattus sp., melomys and the bush rat (*Rattus fuscipes*) (Queensland Government, 2015c). There are marsupial species including antechinus, pademelon, bandicoot, gliders, possums and the Koala (*Phascolarctos cinereus*) (Queensland Government, 2015c). Wildlife camera footage from the Gympie National Park site confirmed the presence of the Yellow-footed Antechinus (*Antechinus flavipes flavipes*), Echidna (*Tachyglossus aculeatus*), Swamp Wallaby (*Wallabia bicolor*) and Common Brushtail Possum (*Trichosurus vulpecula*). One wildlife camera was used, it was moved between the sites (for the details of each deployment see Appendix C). These animals forage at night contributing to the sounds of animal movements heard in the recording. Male Koala (*Phascolarctos cinereus*) calls were annotated. The Red Fox (*Vulpes vulpes*) a feral species to Australia was annotated in the recording (see Appendix B).

Woondum National Park has four species of rodent, seven species of bat and other species including pademelon, wallabies, bettongs, possums, gliders, antechinus, and the Koala and the Echidna (Queensland Government, 2015b). The Swamp Wallaby (*Wallabia bicolor*) and a rodent species were detected using the wildlife camera deployed at the site (Appendix C) and the male Koala (*Phascolarctos cinereus)* was annotated in the Woondum National Park recording.

3.7 SURVEYS OF THE SOURCES OF GEOPHONY

The two sites are mostly sheltered from strong wind due to their position in the landscape. Despite this, each site experiences winds and the recorder detected the sound of wind in the tree canopy and at ground level.

The Gympie National Park site is 50 metres from a ridgeline on a northerly slope. The site has open forest to the southeast, southwest, and scrub further down the slope to the north. The nearby ridgeline is exposed, experiencing breezes and winds from the south and southeast. These are not experienced at the recorder to the same degree. The dry gully to the northeast carries water only after very heavy downpours. A thunderstorm and downpour occurred on the afternoon of the 30 January 2016. The gully was flowing when the batteries were changed on the recorder the next day, more than 19 hours after the storm.

The Woondum National Park site on a north-west facing slope is situated about 100 metres from a normally dry creek. The mountain range to the northeast rises to 430 metres above sea level to a plateau, which provides a buffer from the rain experienced on the eastern coastal side of the range. The Woondum National Park site experiences more rain than the Gympie National Park site due to its proximity to the coast. The creek was flowing on the 31 January 2016 after the heavy downpour on the previous day. The creek was also flowing on Sunday 7th February 2016, eight days after the storm, but was dry a week later on Sunday 14th February 2016.

3.8 SURVEYS OF THE SOURCES OF ANTHROPOPHONY

The human-activities occurring close to the recorders were bushwalking, horse riding and trail-bike riding. The recorders at each site were placed about 50 metres from the tracks to avoid visibility. Four-wheel drive vehicles occasionally pass close to the Gympie National Park site but this was uncommon. At Woondum, vehicle access was restricted from December 2015 when steel barriers and signs were erected. Despite this, motorbikes were commonly heard within the park on weekends. Both sites are below flight paths of domestic aircraft routes between Brisbane and Rockhampton as well as local air traffic.

3.9 SUMMARY

The differences in tree species, vegetation structure and climatic conditions accounts for differences in bird and other species observed in the recordings and at the sites. The more open woodland at Gympie National Park appears to be more conducive for the larger birds such as the Laughing Kookaburra (*Dacelo novaeguineae*), Pied Currawong (*Strepera graculina*), Australian Magpie (*Cracticus tibicen*), Pied Butcherbird (*Cracticus nigrogularis*), and Grey Butcherbird (*Cracticus torquatus*) and has a greater abundance of honeyeater species. The wetter more closed environment of the Woondum National Park site is preferable for birds such as the Australian Logrunner (*Orthonyx temminckii*), Red-browed Treecreeper (*Climacteris erythrops*) and the Red-browed Finch (*Neochmia temporalis*).

Human presence at the two sites varied. The Woondum National Park site was the more frequented. This was mostly in the form of recreations such as motorbike and horse riding. Woondum National Park is more closely located to population centres at the northern end of the Sunshine Coast, which could account for the greater number of visitors, although visitor numbers at the two recording sites were very low.

Chapter 4

Signal Acquisition and Processing

Stereo wave audio files were collected by the author every 7-10 days, the battery life determined the frequency of the collection. The files were securely stored each week. The site visits and data collection required between three and four hours per week due to the time taken to drive the unsealed roads and to walk to the recorders. An additional two hours was required to back-up and upload the data each week.

Quality control was conducted on the data after microphone problems were noticed and the extent of microphone malfunction was assessed. One microphone on each recorder malfunctioned following moderate and heavy rain. Feature extraction was performed on the audio recordings by calculating the summary and spectral acoustic indices on one-minute audio segments. The summary acoustic indices form the datasets used in clustering. The spectral acoustic indices were used to produce the LDFC spectrograms. The acoustic indices were originally calculated on both the left and right channels, but were recalculated on the unaffected channels following the assessment of the microphone problems, details are provided in Chapter 5.

4.1 OVERVIEW

This chapter defines the recording protocols, the quality control performed on the recordings, how the recordings were prepared for feature extraction, and a concise description of each of the acoustic indices calculated. This chapter also describes the preparation of the datasets used in this research. The first of these datasets consisting of twelve days of data will be used in Chapter 7 to determine the clustering method to be used on the thirteen-month dataset.

4.2 RECORDING AND DATA STORAGE PROTOCOLS

The recorders recorded continuously from midnight on the 22 June 2015 to midnight on the 23 July 2016. The recording parameters are given in Table 4.1. A 22.05 kHz sampling rate was chosen because most biophonic sounds are in the range from 2 to 11 kHz (Qi et al., 2007, p.202). The schedule instructed the recorders to start recording at midnight and to record for 24 hours before repeating the schedule indefinitely. The recorders collect 88,200 bytes of data per second (2 channels × 2 bytes × sampling rate) (Wildlife Acoustics, 2013) or 53.3 GB each week per site. Over the period of the 13 months, almost 6 TB of data was collected.

Table 4.1 Recording Parameters

Variable	Value
Audio Recorder	Song Meter 2 (SM2+) (Wildlife Acoustics) (see Table 3.2)
Sampling rate	22,050 Hz
Bit rate	16 bit
Microphone	Omnidirectional - frequency response flat (20 Hz – 20 kHz)
Stereo	Left and right channels
File format	WAV onto SD cards
Power supply	4 × D cell batteries, 1.5 volt
Batteries replaced	Usually 7 days but occasionally up to 10 days
Height/position	1.5 metres attached to a tree

The recording schedule produced three 2 GB wav files of length just under 6 hours 45 minutes and one shorter 1.3 GB wav file of length 3 hours 45 minutes. Although this provided the coverage of the 24-hour period, the three breaks during the day did not coincide with the end of a minute. This resulted in the analysis of partial minutes at the changeover of files. For all future recordings, this should be avoided by recording 6-hour blocks commencing at midnight, 6 am, 12 noon and 6 pm, ensuring the analysis will be performed on full minutes.

The wave files were transferred to the Queensland University of Technology high performance computer (HPC) file share from which the analysis of the acoustic indices was made using the dedicated big data server. The Queensland Cyber Infrastructure Foundation (QCIF) provides the resources for the Ecosounds website (Truskinger et al., 2014).

4.3 QUALITY CONTROL

Shortly after the commencement of the recording, microphone malfunction was noted in one microphone on each recorder, it appeared to follow rain. Following discussions with the members of the QUT Ecoacoustics Research Group, it was decided to continue to record with these microphones.

A PCA plot (explained in Chapter 6) produced on the first four months of data calculated from both the left and right channels demonstrated the extent of the problem (Phillips, Towsey & Roe, 2018). A manual examination of the first recording on each day was conducted to determine the extent of the problem. The malfunction occurred consistently in one microphone after rain except in one instance. The one instance occurred in the Gympie National Park recording on the 28, 29 and 30 October 2015 when both microphones experienced malfunction. These three days were removed from the thirteen-month dataset as a result.

The issue of microphone malfunction has not been addressed to any extent in the academic research literature, although Blumstein et al. (2011) mentions the need to protect the recording units and microphones from rain. Chapter 5 explains the development of a decision tree classifier for the detection of microphone malfunction. As this method was developed at the end of the research it was not used to detect microphone malfunction in the recordings. Manual inspection was instead used to make a decision to remove the affected channel and recalculate the acoustic indices on one channel only.

4.4 PRE-PROCESSING OF RECORDINGS

Pre-processing of recordings involved the application of a Hamming window to each frame (window length 512, 0% overlap) in a one-minute audio segment before the calculation of a Fast Fourier transform (FFT) (Cooley & Tukey, 1965). A Hamming window is a mathematical function that frames a small region of signal to allow examination without interference from the adjacent signal (Bojkovic, Bakmaz & Bakmaz, 2017). The FFT transforms the signal to the frequency domain. The matrix of Fourier coefficients forms the amplitude spectrogram.

The recording sampling rate (22 050 Hz) and window length (512) defines the frame rate (22050 / 512 = 43.06) frames per second or 2583 frames per minute) and the time-interval (23.22 milliseconds). The number of frequency bins (256) is dependent on the trade-off between the frequency and time precision governed by the uncertainty principle (Beecher, 1988; Gabor, 1947), also see (Sueur, 2018a p.312-313). The frequency range of the recording was 0 to 11.025 kHz.

Each spectrum was smoothed with a moving average window (width = 3) to reduce spectral variance. The adaptive level equalisation algorithm (Lamel et al., 1981) as described in Towsey (2017) is used for noise removal. The *wave envelope* is determined from the maximum absolute amplitude in each frame; which in our case is 512 samples. The *decibel envelope* is calculated using Equation 8, where A are the amplitudes in the wave envelope.

$$dB = 20 \times \log_{10} A \qquad (8)$$

The *decibel spectrogram* required for the calculation of particular acoustic indices is calculated using Equation 8, where A are the Fourier coefficients (Figure 4.1). The *energy spectrogram* is formed by squaring the amplitude spectrogram values following noise reduction (Figure 4.1).

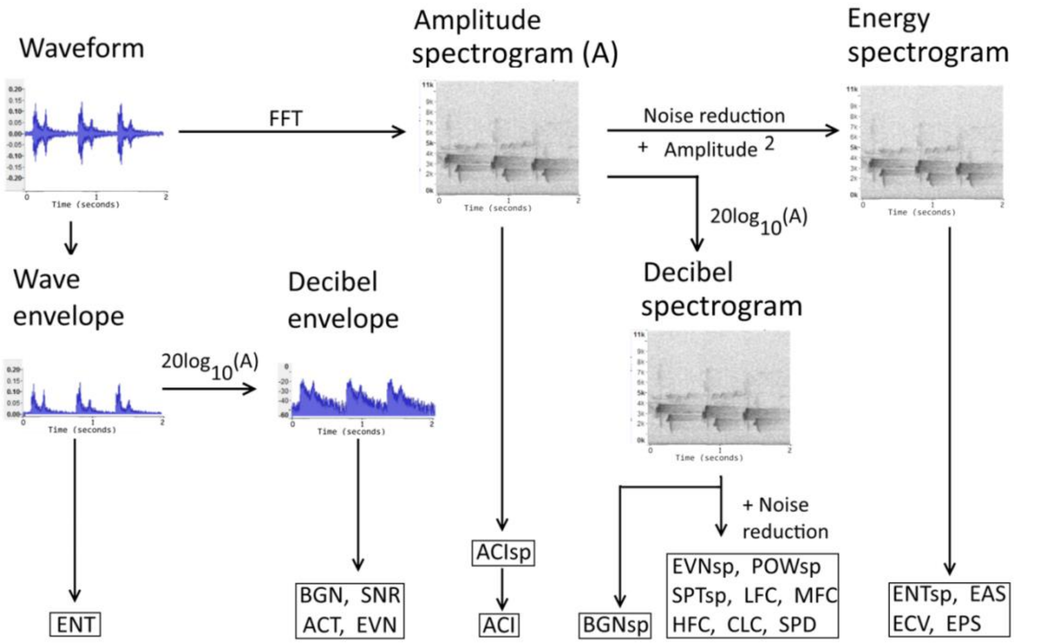


Figure 4.1: A schematic diagram showing how spectral and summary acoustic indices are derived. The acoustic indices are shown in the boxes as a three-letter code; those with a suffix ‘sp’, for example ACIsp are spectral indices. The three-letter codes are defined in Sections 4.6 and 4.7.

4.5 CALCULATION OF THE ACOUSTIC INDICES

Acoustic indices are calculated from the one-minute amplitude, energy or decibel spectrograms, or the wave envelope (Figure 4.1). Acoustic indices are either spectral or summary. *Spectral indices* are vectors that summarise different aspects of the acoustic energy within a predefined frequency band and time period. The *spectral acoustic* indices are denoted by a three-letter code with a suffix ‘sp’, for example ACIsp is the spectral acoustic index of the Acoustic Complexity Index (Section 4.6.1). Alternatively, *summary indices* provide a single statistic across a broad frequency range to represent different aspects of the acoustic energy within that time-period, typically one minute. The summary acoustic indices are denoted by a three-letter code with no suffix, for example ENT is the summary acoustic index of the Temporal Entropy Index (Section 4.7.2). A concise description of the six spectral and fourteen summary indices used in this study is provided. Refer to Towsey (2017) for a comprehensive description. The acoustic indices calculations are performed using the Audio Analysis Software Version 16.06.3430.0 (Towsey, Truskinger & Roe, 2016).

4.6 THE SPECTRAL ACOUSTIC INDICES

Spectral indices retain frequency domain information because they summarise within frequency bins rather than across a broad frequency range. An outline of each spectral index used in this study is given below.

4.6.1 Acoustic Complexity Index (ACIsp)

From the amplitude spectrogram, within each frequency bin, the sum of the absolute fractional changes between adjacent amplitude values over the period of one minute divided by the sum of the amplitudes is calculated (see Equation 1, Section 2.5.1) (Pieretti et al., 2011) to a give ACI_f for each frequency bin.

4.6.2 Entropy (ENTsp)

Normalise to unit area the values in the energy spectrogram within each frequency bin. The resulting vector is used as the pmf(t) in Equation 3 (Section 2.5.1) to find H_t(f) for each frequency bin, f (Towsey, 2017). Equation 9 is used to find the 'energy concentration' (Towsey, 2017).

$$\mathrm{ENTsp}[\mathrm{f}] = 1 - H_t[\mathrm{f}] \qquad (9) \qquad (\mathrm{Towsey}, 2017).$$

4.6.3 Acoustic Events (ENVsp)

Acoustic Events are the count of the number of times the noise-reduced decibel spectrogram cell value crosses the 3 dB threshold from below within a one-minute period in each frequency bin (Towsey, 2017).

4.6.4 Background Noise (BGNsp)

The spectral Background Noise provides a 'noise profile', it is calculated across each minute in each frequency bin of the decibel spectrogram (Towsey, 2017). There are four steps to find the Background Noise for each frequency bin BGN(f) (Towsey, 2017):

1. For each frequency bin, calculate a 100-bin histogram by aligning the minimum and maximum values in the histogram bins with those in the frequency bin.
2. Apply a moving average filter to smooth the histogram (window = 5).

3. Find the modal bin, the bin containing the maximum count. Set the modal bin to the 95th bin if it is in the range of 96 to 100.
4. The BGN(f) is equal to the decibel value corresponding to the bin identified in step 3.

BGNsp is then found by smoothing the BGN(f) values calculated for each frequency bin with a moving average filter (window = 5).

4.6.5 Power (POWsp)

Power is the maximum decibel value in each frequency bin minus the BGNsp value across the minute for that frequency bin (Towsey, 2017).

4.6.6 Spectral Peak Tracks (SPTsp)

The Spectral Peak Tracks index counts the number of spectral peaks across the minute in the decibel spectrogram by finding the spectral peaks greater than 6 dB within each frequency bin. A peak occurs if the value in one frequency bin is greater those in adjacent frequency bins. To find the spectral peak tracks for the frequency bin (f), find the sum of all decibel values of all identified peaks and divide by the number of frames across the minute (Towsey, 2017).

4.7 THE SUMMARY ACOUSTIC INDICES

Summary acoustic indices differ from spectral acoustic indices in that they are scalar values (not vectors) representing the measured variable across a broad frequency range. A brief description of each summary index used in this study is below.

4.7.1 Acoustic Complexity Index (ACI)

The Acoustic Complexity Index is the average of the ACIsp values (Section 4.6.1) in the frequency range of 1 to 8 kHz. Removing frequencies below 1 kHz eliminates most acoustic energy from wind and anthropogenic sources such as aircraft (Towsey, 2017).

4.7.2 Temporal Entropy (ENT)

Temporal Entropy measures the dispersal of acoustic energy over time; it is calculated as described for ENTsp (Section 4.6.2), but across the wave envelope (Towsey, 2017). Calculate temporal entropy using Equation 3 (Section 2.5.1). The temporal entropy (a measure of acoustic energy dispersal) was converted to ‘energy concentration’ using Equation 9 (Section 4.6.2).

4.7.3 Events per Second (EVN)

Events per Second is determined from the number of times the decibel envelope crosses a BGN + 3 dB threshold from below and then averaging this to per second (Towsey, 2017) see Figure 4.2.

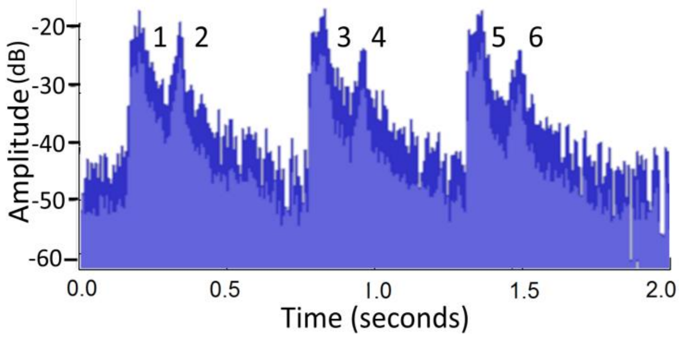


Figure 4.2 Events per second is the average number of events occurring per second in a decibel waveform. The example shows a two-second segment of the decibel waveform of a Yellow-faced Honeyeater (*Caligavis chrysops*) call. In this case, there would be approximately 3 events per second if the call continued consistently across one minute. Image produced using Audacity (Ash et al., 2017).

4.7.4 Background Noise (BGN)

The Background Noise is calculated from the decibel waveform (Towsey, 2017). There are three steps to find BGN (Lamel et al., 1981; Towsey, 2017):

1. Determine a 100-bin histogram by aligning the minimum and maximum values in the histogram bins with those in the decibel waveform. If the minimum value is less than -80 decibels, reset this value to -80.
2. Apply a moving average filter to smooth the histogram (window = 5 or 7).
3. Find the modal value of the histogram; this is the average noise in the minute and the value used as BGN.

4.7.5 Signal to Noise ratio (SNR)

The Signal to Noise ratio is the difference between the BGN value (Section 4.7.4) and the maximum value in the decibel envelope (Towsey, 2017).

4.7.6 Activity (ACT)

Activity is the fraction of values in the one-minute decibel envelope that exceed 3 decibels above the BGN value (Section 4.7.4) (Towsey, 2017). Figure 4.3 shows the waveform of a dusk cicada chorus, these sounds have high ACT values because the sound is maintained above the BGN + 3 dB threshold.

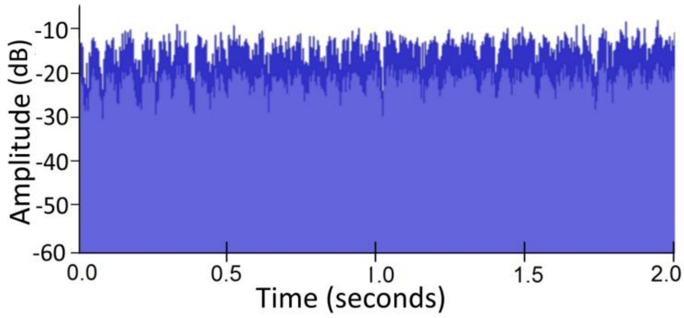


Figure 4.3 The waveform of the continuous sound of a cicada during the dusk chorus. Activity (ACT) measures the proportion of the one-minute segment where the signal remaining above BGN + 3 dB. Continuous sounds such as this have high activity values. Image produced using Audacity (Ash et al., 2017).

4.7.7 High Frequency Cover (HFC)

High Frequency Cover is the fraction of the noise-reduced decibel spectrogram cells in the high frequency band (8–11.025 kHz) that exceed 3 dB above the background noise (Towsey, 2017).

4.7.8 Mid Frequency Cover (MFC)

Mid Frequency Cover is the fraction of the noise-reduced decibel spectrogram cells in the mid frequency band (1–8 kHz) that exceed 3 dB above the background noise (Towsey, 2017).

4.7.9 Low Frequency Cover (LFC)

Low Frequency Cover is the fraction of the noise-reduced decibel spectrogram cells in the frequency band below 1 kHz that exceed 3 dB above the background noise (Towsey, 2017).

4.7.10 Entropy of the Average Spectrum (EAS)

Using the energy spectrogram, average the energy values in each frequency bin between 1 and 8 kHz to find the mean energy spectrum (Towsey, 2017). Use Equation 4 (Section 2.5.1) to find H_a where pmf(f) is the mean energy spectrum and N is the number of frequency bins, before using EAS = 1 – H_a (Towsey, 2017).

4.7.11 Entropy of the Spectral Peaks (EPS)

The Entropy of the Spectral Peaks measures the concentration of spectral maxima within frames per frequency bin in the range from 1 to 8 kHz in the energy spectrogram across one-minute (Towsey, 2017).

This is calculated in three steps:

1. Within each frame, locate the spectral maxima, the bin that contains the maximum amplitude.
2. Count the spectral maxima for each frequency bin.
3. Use Equation 4 (Section 2.5.1) to find H_p, with the frequency bins in the band 1-8 kHz, where pmf(f) is the count of the spectral maxima and N is the number of frequency bins. Convert H_p to EPS using EPS = 1 – H_p (Towsey, 2017).

4.7.12 Entropy of Coefficient of Variation (ECV)

The Entropy of Coefficient of Variation is calculated in a similar way to EAS. The spectrum upon which the entropy is calculated is equal to the variance of the energy values divided by the mean of energy values in each frequency bin between 1 and 8 kHz in the energy spectrogram (Towsey, 2017). H_c is calculated using Equation 4 (Section 2.5.1) before using ECV = 1 – H_c (Towsey, 2017).

4.7.13 Cluster Count (CLC)

The Cluster Count uses clustering to quantify the degree of structure in the mid-frequency band (1–8 kHz) of a one-minute segment. It is expected that, the greater the diversity of bird species, the greater the cluster count. A brief summary of the six-step procedure given in Towsey (2017) is provided below:

1. Average adjacent frequency bins of the noise-reduced decibel spectrogram in groups of three to reduce frequency bins from 162 to 54 in the mid-frequency band.
2. Convert the spectrum in each frame to a binary vector using a 6 dB threshold.
3. The binary vector becomes part of the training spectra if the sum of its elements is greater than one.
4. If the number of training spectra does not exceed eight the cluster count is set to zero.
5. If the number of training spectra exceeds eight, cluster these using the method described in Towsey (2017) to determine the number of spectral clusters.

6. Discard any clusters containing a low number of members (< 3) leaving the count of the remaining clusters.

4.7.14 Spectral Peak Density (SPD)

The Spectral Peak Density (SPD) uses the decibel spectrogram in a topographic way to locate and measure the number of cells that form local amplitude maxima (Towsey, 2017). The three-step procedure given in Towsey (2017) is provided below:

1. One frame at a time, locate all cells with an amplitude exceeding 6 dB. From these, select cells with an amplitude greater than its neighbours in adjacent frequency bins. Note this is the same as the first step when calculating SPTsp (Section 4.6.6).
2. Count the spectrogram cells that fulfil the criteria in step 1 across all frames in the one-minute audio segment.
3. Divide the number of cells from step 2 by the number of frequency bins.

4.8 THE PREPARATION OF THE DATASETS

The preparation of two datasets derived from the acoustic indices is explained, starting with the description of the twelve-day dataset. The preparation of the thirteen-month dataset is then described; this dataset was used in the clustering. The twelve-day dataset was selected from the first 111 days of data. The selected twelve days plays a role in the selection of the clustering method covered in Chapter 7, and in optimising the clustering of the thirteen-month clustering.

4.8.1 The Twelve-day Dataset

The twelve-day dataset was prepared from the summary acoustic indices calculated on each consecutive one-minute segment. Twelve-days were selected from the 22 June 2015 to the 11th October 2015 (the first 111 days). The twelve summary acoustic indices calculated were Acoustic Complexity Index (ACI), Activity (ACT), Background Noise (BGN), Entropy of Average Spectrum (EAS), Entropy of Peaks Spectrum (EPS), Entropy of the Spectrum of Coefficients of Variation (ECV), Events per Second (EVN), High Frequency Cover (HFC), Low Frequency Cover (LFC), Mid Frequency Cover (MFC), Signal-to-Noise Ratio (SNR) and Temporal Entropy (ENT). The twelve-day dataset was used to test four clustering algorithms (Chapter 7).

The twelve days, six days from each site were days with no rain and very little wind and were selected in four groups of three days. The criteria for the selection of the twelve days are listed below.

1. The three days in each group must be as near as possible to three consecutive days.
2. The days must not have any rain and as little as possible wind.
3. The days from each recording site should be the same 24-hour periods.
4. The two groups of days from each site should be separated in time by about one month at minimum.

Criterion 1 increases the probability that the three-day groups have a similar acoustic content (Sankupellay et al., 2015). Criterion 2 ensures the test dataset is mostly biophony with as little geophony as possible. Criterion 3 increases the difficulty of the test by introducing the chance that corresponding days from each regionally near sites could be more similar than the expected differences between sites. Criterion 4 is expected to introduce seasonal differences between the two groups from each site.

The twelve-day dataset was chosen by examining LDFC spectrograms of each day and eliminating days with rain (for an example see Figure 6.1) or wind. Moderate to strong wind and moderate to heavy rain were identified in the LDFC spectrograms and removed from the sample of days. The twelve-days that met the four criteria are provided in Table 4.2. Here the four groups are listed, it should be noted the time separation between the mid-winter and early-spring days.

Table 4.2 The dates of the twelve-day dataset. The four groups of days consist of two groups of corresponding days, a set of three days from mid-winter and another set of three days from early spring. Each day is numbered for future reference.

		Site differences	
		Gympie National Park	**Woondum National Park**
Seasonal differences	**Mid-winter**	July 30, 2015 (day 1) July 31, 2015 (day 2) August 1, 2015 (day 3)	July 30, 2015 (day 7) July 31, 2015 (day 8) August 1, 2015 (day 9)
	Early-spring	August 31, 2015 (day 4) September 1, 2015 (day 5) September 4, 2015 (day 6)	August 31, 2015 (day 10) September 1, 2015 (day 11) September 4, 2015 (day 12)

Light rain was not easy to distinguish in the LDFC spectrograms, so a manual search of the recordings was also conducted. From all possible days, a list of consecutive days or days separated by no more than one or two days was made. These days were further examined using Audacity (Ash et al., 2017) to determine whether they contained rain or wind missed in the initial examination.

The twelve-day dataset was formed from the feature vectors from the twelve days in Table 4.2. The twelve-day dataset containing 17,280 vectors of acoustic indices was used to choose a clustering method (see Chapter 7) to be used to cluster the thirteen-month dataset.

These indices were normalised between 2 and 98 percentile bounds and scaled between 0 and 1. A correlation matrix (Table 4.3) was used to reduce the twelve normalised summary acoustic indices derived from the twelve days of data to seven. One of each pair of highly correlated indices (Pearson's correlation > 0.75), was removed. The seven remaining summary indices were Acoustic Complexity (ACI), Background Noise (BGN), Events per second (EVN), Entropy of Peaks Spectrum (EPS), Entropy of Coefficient of Variation (ECV), Low Frequency Cover (LFC), and Signal-to-Noise Ratio (SNR). The calculation of the acoustic indices used amplitude values in the left and right channels.

4.8.2 The Thirteen-Month Dataset

The thirteen-month dataset was prepared following the basic procedure already explained. However, the visualisation of the first 111 days revealed the significance of problems with one of the microphones on each recording unit (Phillips et al., 2018). Consequently, the spectral and summary acoustic indices were recalculated on one channel only.

After the recalculation of the acoustic indices, the summary indices for the 398 days for the two sites provided a dataset of 1,141,147 instances. Fourteen summary indices were calculated, these were Acoustic Complexity Index (ACI), Activity (ACT), Background noise (BGN), Cluster Count (CLC), Entropy of Average Spectrum (EAS), Entropy of Peaks Spectrum (EPS), Entropy of the Spectrum of Coefficients of Variation (ECV), Events per Second (EVN), High Frequency Cover (HFC), Low Frequency Cover (LFC), Mid Frequency Cover (MFC), Temporal Entropy (ENT), Signal-to-noise ratio (SNR), and Spectral Peak Density (SPD). Two corrupted recordings were padded with NA values along with the missing minutes from the weekly battery changes.

These indices were normalised between 1.5 and 98.5 percentile bounds and scaled between 0 and 1. A correlation matrix (Table 4.4) of the normalised summary indices was used to remove one pair of each highly correlated indices (Pearson's correlation > 0.7). A high correlation was indicated by the value of 0.7 (Hinkle, Wiersma & Jurs, 2003 p.109), this value is commonly used (Gage et al., 2017b). The twelve acoustic indices remaining were Activity (ACT), Acoustic Complexity Index (ACI), Background Noise (BGN), Cluster Count (CLC), Entropy of Average Spectrum (EAS), Entropy of Peaks Spectrum (EPS), Entropy of the Spectrum of Coefficients of Variation (ECV), Events per Second (EVN), High Frequency Cover (HFC), Low Frequency Cover (LFC), Mid Frequency Cover (MFC) and Signal to Noise ratio (SNR).

4.9 SUMMARY

This chapter provided the recording protocols, the details of the pre-processing of the recordings, a description of all acoustic indices used in this research and the preparation of the datasets. The calculation of the spectral acoustic indices facilitates the production of the LDFC spectrograms (Towsey et al., 2014b). The calculation of the summary acoustic indices allows the formation of two datasets, one twelve-day dataset that will be used to test four clustering methods (Chapter 7) and a second containing the thirteen-months of data that will be clustered (Chapter 8).

This chapter also provided a rationale for the selection of the twelve-day test dataset. This dataset is central to the selection of a clustering method to be used on the thirteen-month dataset and in optimising the clustering of the thirteen-month dataset.

Table 4.3 Correlation Matrix (twelve-day dataset)

	BGN	**SNR**	ACT	**ENV**	HFC	MFC	**LFC**	**ACI**	ENT	EAS	**EPS**	**ECV**
BGN	**1.000**	0.081	0.154	0.171	0.316	0.299	0.240	0.218	0.078	0.308	0.531	0.192
SNR	0.081	**1.000**	0.672	0.610	0.570	0.519	0.310	0.646	**0.859**	0.490	0.427	0.420
ACT	0.154	0.672	**1.000**	**0.878**	0.502	0.486	0.597	0.528	0.690	0.313	0.281	0.237
EVN	0.171	0.610	**0.878**	**1.000**	0.504	0.482	0.508	0.540	0.562	0.317	0.287	0.215
HFC	0.316	0.570	0.502	0.504	**1.000**	**0.784**	0.272	**0.839**	0.508	0.673	0.714	0.410
MFC	0.299	0.519	0.486	0.482	**0.784**	**1.000**	0.310	**0.814**	0.498	0.578	0.631	0.341
LFC	0.240	0.310	0.597	0.508	0.272	0.310	**1.000**	0.254	0.357	0.149	0.033	0.140
ACI	0.218	0.646	0.528	0.540	**0.839**	**0.814**	0.254	**1.000**	0.623	0.607	0.675	0.370
ENT	0.078	**0.859**	0.690	0.562	0.508	0.498	0.357	0.623	**1.000**	0.329	0.329	0.311
EAS	0.308	0.490	0.313	0.317	0.673	0.578	0.149	0.607	0.329	**1.000**	**0.763**	0.635
EPS	0.531	0.427	0.281	0.287	0.714	0.631	0.033	0.675	0.329	**0.763**	**1.000**	0.529
ECV	0.192	0.420	0.237	0.215	0.410	0.341	0.140	0.370	0.311	0.635	0.529	**1.000**

BGN = Background Noise, **SNR** = Signal to Noise ratio; ACT = Activity; **EVN** = Events per Second; HFC = High Frequency Cover; MFC = Mid Frequency Cover; **LFC** = Low Frequency Cover; **ACI** = Acoustic Complexity Index; ENT = Temoral Entropy; EAS = Entropy of Average Spectrum; **EPS** = Entropy of Peaks Spectrum; **ECV** = Entropy of the Spectrum of Coefficients of Variation.The seven summary indices marked in bold were selected for the twelve-day dataset.

Table 4.4 Correlation Matrix (thirteen-month dataset)

	BGN	**SNR**	**ACT**	**EVN**	**HFC**	**MFC**	**LFC**	**ACI**	ENT	**EAS**	**EPS**	**ECV**	**CLC**	SPD
BGN	**1.000**	0.186	0.359	0.333	0.438	0.393	0.431	0.178	0.212	0.339	0.567	0.006	0.551	0.509
SNR	0.186	**1.000**	0.567	0.521	0.320	0.445	0.231	0.611	**0.869**	0.380	0.390	0.009	0.475	0.445
ACT	0.359	0.567	**1.000**	0.699	0.451	0.502	0.479	0.285	0.486	0.220	0.358	0.009	0.452	0.555
EVN	0.333	0.521	0.699	**1.000**	0.276	0.390	0.405	0.498	0.492	0.273	0.347	0.051	0.485	0.420
HFC	0.438	0.320	0.451	0.276	**1.000**	0.573	0.338	0.148	0.303	0.316	0.458	0.040	0.448	**0.783**
MFC	0.393	0.445	0.502	0.390	0.573	**1.000**	0.424	0.459	0.415	0.469	0.698	0.028	0.690	**0.936**
LFC	0.431	0.231	0.479	0.405	0.338	0.424	**1.000**	0.079	0.206	0.258	0.314	0.021	0.313	0.538
ACI	0.178	0.611	0.285	0.498	0.148	0.459	0.079	**1.000**	0.695	0.319	0.421	0.043	0.596	0.361
ENT	0.212	**0.869**	0.486	0.492	0.303	0.415	0.206	0.695	**1.000**	0.289	0.350	0.038	0.457	0.410
EAS	0.339	0.380	0.220	0.273	0.316	0.469	0.258	0.319	0.289	**1.000**	0.565	0.024	0.440	0.497
EPS	0.567	0.390	0.358	0.347	0.458	0.698	0.314	0.421	0.350	0.565	**1.000**	0.145	0.625	**0.716**
ECV	0.006	0.009	0.009	0.051	0.040	0.028	0.021	0.043	0.038	0.024	0.145	**1.000**	0.051	0.007
CLC	0.551	0.475	0.452	0.485	0.448	0.690	0.313	0.596	0.457	0.440	0.625	0.051	**1.000**	0.667
SPD	0.509	0.445	0.555	0.420	**0.783**	**0.936**	0.538	0.361	0.410	0.497	**0.716**	0.007	0.667	**1.000**

BGN = Background Noise, **SNR** = Signal to Noise ratio; **ACT** = Activity; **EVN** = Events per Second; **HFC** = High Frequency Cover; **MFC** = Mid Frequency Cover; **LFC** = Low Frequency Cover; **ACI** = Acoustic Complexity Index; ENT = Temoral Entropy; **EAS** = Entropy of Average Spectrum, **EPS** = Entropy of Peaks Spectrum; **ECV** = Entropy of the Spectrum of Coefficients of Variation, **CLC =** Cluster Count; SPD = Spectral Peak Density. The twelve summary indices marked in bold were selected for the thirteen-month dataset.

Chapter 5

Automatic Microphone Problem Detection

The detection of microphone problems is an important quality control measure that must be checked and if necessary acted on before the calculation of the acoustic indices (feature extraction). It was noted shortly after the commencement of this project that one of the microphones on each of the recorders was malfunctioning following rain. Advice was sought from the members of the QUT Ecosounds Research Group. The advice was that this had not been observed before and to continue recording with these microphones.

This chapter describes how microphone problems can be detected manually and how a decision tree was built to automatically detect microphone malfunction in very-long-duration audio recordings. The decision tree performs to an accuracy of 83.4% in detecting minutes affected by microphone malfunction.

5.1 OVERVIEW

This chapter focuses on the detection of problems associated with microphone failure in very-long-duration audio recordings. The detection of microphone problems in short duration recordings is relatively easy to detect by comparing the spectrograms of each channel. However, in very-long-duration audio recordings this becomes extraordinarily time-consuming and, if dealing with tens or hundreds of very-long-duration audio recordings, it would be impossible.

Under the field conditions in this study, the interior of the recording boxes containing the electronics remained dry, however one microphone on each recorder malfunctioned following moderate to heavy rain. Microphone failure is not well documented. However; it is considered probable in very-long recordings (Farina et al., 2018) and was discussed as a serious issue at the Australasian Ecoacoustics Workshop in 2017. Turgeon, Van Wilgenburg and Drake (2017) did not discuss microphone failure but found that microphones lose sensitivity during field use.

5.2 MANUAL DETECTION OF MICROPHONE PROBLEMS

When microphone failure occurs, its detection by manual inspection of spectrograms, such as those in Figure 5.1, is relatively straightforward. The grey-scale spectrograms show the left and right channel of two short segments of audio. The first pair of spectrograms (Figure 5.1a) demonstrates two functioning microphones as is evident by the similarity of the spectrograms of the left and right channels. The second pair of spectrograms (Figure 5.1b) demonstrates a malfunctioning left microphone and a functioning right microphone. The left channel also indicates that the malfunctioning microphone generates broadband noise in the channel.

A manual inspection of one file per day containing the morning chorus was completed using Audacity (Ash et al., 2017). From the inspection, it became evident that the microphone failure occurred during or following moderate to heavy rain. Only one microphone on each recording unit was found to malfunction, except for the failure of both microphones on the Gympie National Park unit on the 28th October 2015 following rain. On this occasion, both microphones malfunctioned until the right microphone recovered after three days.

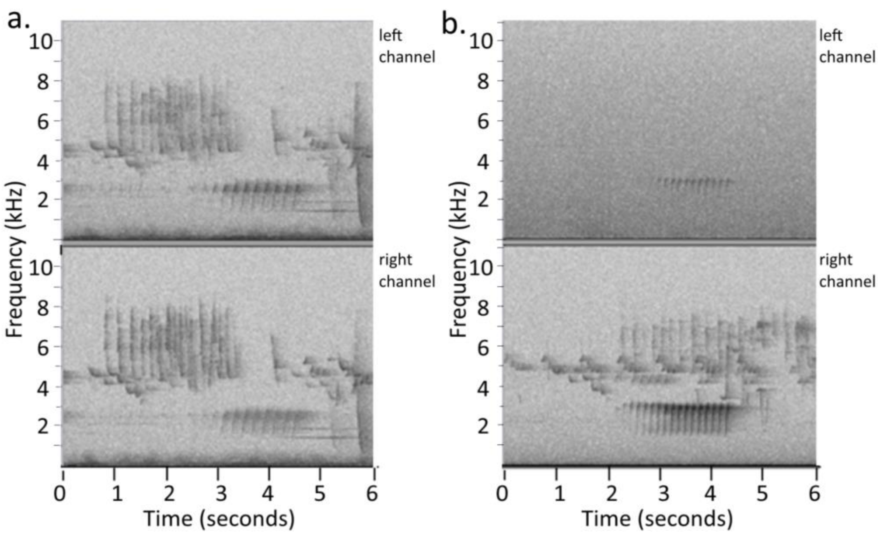


Figure 5.1a. The left and right channels from the 15 July 2015 at 6:21 am when both microphones were functioning correctly showing similar events in each channel.

b. The left and right channels from the 25 July 2015 at 6:38 am when the left microphone had malfunctioned. Notice the difference in noise between the left and right channels. The six-second spectrograms were produced using Audacity (Ash et al., 2017).

Microphone malfunction was more pronounced in the Gympie National Park recording. In January 2016, the malfunctioning microphones on each unit were replaced. The replacement microphone on the Gympie National Park unit did not function; it was replaced with another microphone on the 24 January 2016. Fortunately, one microphone on each recorder functioned for most of the thirteen months. However, the microphones on the Woondum National Park unit showed some degradation during the last two months of recording. The clustering was performed after the acoustic indices were recalculated on the one channel.

During the manual inspection, the recording files were assessed as having one of three attributes, either ‘left affected’, ‘both’ or ‘not’. ‘Left affected’ indicates a problem with the left microphone. ‘Both’ indicates that both microphones have malfunctioned and ‘not’ indicates there was no problem with the microphones. These labels are used to build the decision tree in Section 5.4.

5.3 AUTOMATIC DETECTION OF MICROPHONE PROBLEMS

Manual inspection is time-consuming and impractical for long-duration recordings. Hence, a method of automatic detection is needed. A number of acoustic features were investigated but the two that showed the most discrimination between a functioning and non-functioning microphone were zero-crossing rate and a measure of the loudness between the channels.

5.3.1 Using Zero Crossing Rate to Detect Microphone Problems

The zero-crossing rate (ZCR) measures the average number of times per second the waveform crosses the zero amplitude value. The ZCR for a degraded microphone generally is higher and holds a stable value compared to an unaffected channel (see the blue line in Figure 5.2).

Figure 5.2a shows the plot of the ZCR values calculated on the left and right channels of each one-minute segment of the Gympie National Park recording on the 22 August 2015 between 1:32 pm and 8:17 pm. The left microphone (blue line) has malfunctioned and is responding very little to the environmental sound. When the left channel was listened to, it was mostly noise. There is a short period of light rain 30 minutes into the recording. At 5:42 pm there is a loud Laughing Kookaburra chorus which drops the zero crossing rate and at 5:52 pm, insects start calling raising the zero-crossing rate significantly. The left channel shows very little difference in the zero crossing rate throughout this series of events, indicating the failure of the left microphone.

Figure 5.2b shows the ZCR values of two functioning microphone channels calculated on one-minute segments recorded at the Gympie National Park site on the 10 November 2015 between 1:32 pm and 8:17 pm. This plot shows a close correspondence in ZCR values between the left and right channels throughout the recording, indicating functioning microphones.

5.3.2 Using Channel Decibel Difference to Detect Microphone Problems

The second acoustic feature used to determine microphone malfunction was the channel decibel difference. This feature measures the difference between the channels by calculating the average of the frame-by-frame amplitudes within each one-minute segment in each channel and then finding the absolute difference between these values.

Figure 5.2c shows the decibel difference for the period from 1:32 pm to 8:21 pm on the 22 August 2015 at Gympie National Park. A large difference above 4 dB as shown in Figure 5.2c indicates a problem in one of the microphones. Two functioning microphones have a low decibel difference between the channels. Figure 5.2d shows a consistently low decibel difference indicating two functioning microphones.

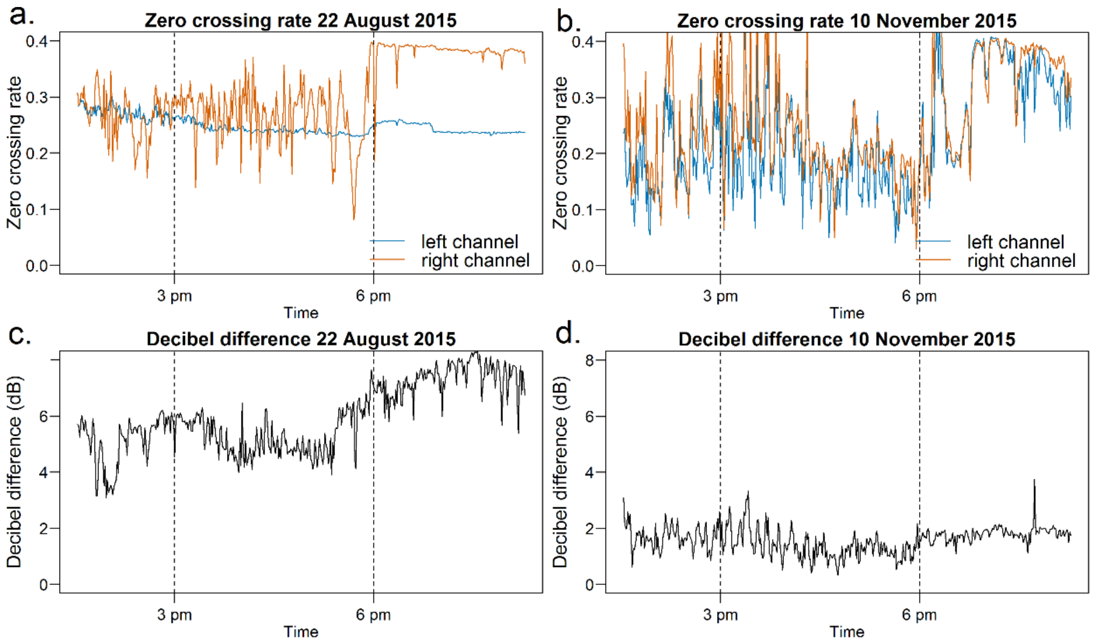


Figure 5.2a & c. Zero-crossing rate and the decibel difference between the malfunctioning left channel and the functioning right channel on the 22 August 2015. b. & d. Zero-crossing rate and the decibel difference between two functioning microphones on the 10 November 2015. Each example is from the Gympie National Park site and between 1:32 pm and 8:17 pm.

5.4 DECISION TREE CLASSIFIER FOR DETECTING MICROPHONE PROBLEMS

Zero crossing rates are variable across recordings; environmental sound such as the morning chorus will increase this feature as does wind, night time insects, and rain. Aircraft significantly decrease this feature. The ZCR in affected microphone channels will tend to have higher values than those of a functioning microphone when there is no wind or rain as is the case in Figure 5.2a.

The higher ZCR at night in an affected channel can be apparent when there is very little sound. However, because the ZCR responds to the geophonic (wind, rain) and anthropophony (aircraft) the raw values cannot be used directly to determine the microphone malfunction. Instead, the difference in the ZCR values was used to build the decision tree model.

The manual inspection of recording files labelled each file as either “left affected”, “not” or “both”. These labels were assigned to each minute corresponding to each file. Although a file may be labelled as affected, all minutes in that file may not be affected. Microphone malfunction does not commence at the beginning of a recording file, nor recover at the end of a recording file. Due to this, the recording files at the beginning and end of each malfunctioning period were removed from the labelled dataset to avoid any misclassification of minutes.

The dataset had 261,864 instances, the equivalent of almost 182 days, incorporating minutes from the 5 July 5 2015 to the 31 January 2016 from the Gympie National Park unit. Each instance contains three attributes, the two acoustic features, zero-crossing rate difference, and channel decibel difference and the label, either “left affected”, “not” or “both”. Of the 261,864 instances, there were 88,137 instances labelled “left affected” 170,442 instances labelled “not” and 3285 instances of “both”. Using the difference between the left and right zero-crossing rate and the decibel difference a decision tree was built using the C4.5 decision tree classifier (Quinlan, 1992) using the J48 implementation in Weka (Witten et al., 1999). The decision tree implemented was performed using Weka 3.8.0 (Frank, Hall & Witten, 2016) with 10-fold cross validation. The full decision tree model is provided in Figure 5.3.

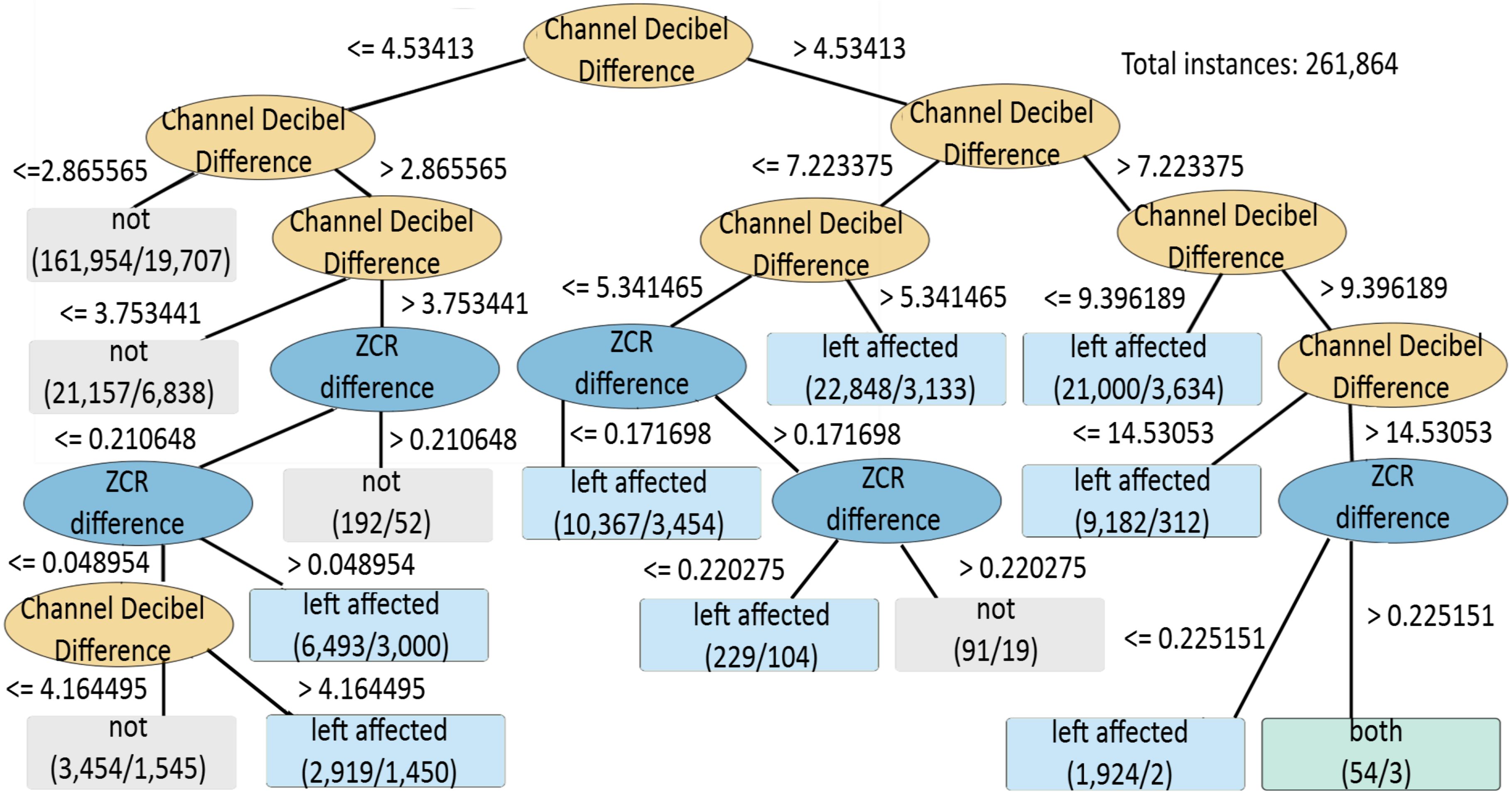


Figure 5.3 Decision Tree Classifier for detecting microphone problems. The decision tree summarises the decisions of the classifier. Elongated ellipses indicate the acoustic features and rectangles indicate the labels provided by the classifier. A range (eg. > 4.53413) for each acoustic feature is provided at each node showing the division of data. The number of correct and incorrect instances in relation to the original labels are provided in brackets (eg. 22,848/3,133).

The number of correctly classified instances is 83.4%. The accuracy of the classification of the three attributes can be determined from the confusion matrix (Table 5.1). The instances, which were labelled “not” affected, were classified accurately at 93.6%. Most of the “both” affected instances were classified as “left affected”, indicating the features used could not always distinguish between “both” and “left affected”.

Table 5.1. The confusion matrix for the decision tree classifier

Classified as			Labelled as
Left affected	**Not affected**	**Both affected**	
58,722 (66.6%)	29,254 (33.2%)	161 (0.1%)	**Left affected**
10,831 (6.4%)	**159, 610 (93.6%)**	1 (0%)	**Not affected**
3,078 (93.7%)	0 (0%)	**207 (6.3%)**	**Both affected**

The “both” case involved the failure of the left channel (as it had failed previously) in addition to the failure of the right channel. When the right microphone malfunctioned, it acted as if it was a low pass filter, passing frequencies below 1 kHz. Some low frequency birds can be heard as well as aircraft but not the birds in the higher frequencies. There was also knocking and other strange sounds that could not be easily attributed to a sound source.

5.5 MICROPHONE CARE

The effect of rain on the microphones was evident; however, what was not clear is why only one microphone on each recorder was affected. Two of the microphones used in this research were new and two had been used previously. It is not clear which microphones were installed on each recorder but it may have been that the older microphones were the ones that were affected by rain. The installation of a small roof to protect the microphones against rain or placing the microphone in a downward position could be another solution (Sueur et al., 2012 p.110-111) if using a single microphone.

5.6 SUMMARY

Manual inspection to determine the extent of microphone problems is unrealistic for long-duration recordings. It was conducted in this case to determine the extent of microphone malfunction. As a result, an automatic method of detection was developed using two acoustic features, zero-crossing rate difference, and channel decibel difference. Channel Integrity plots will be developed later (Chapter 9) to show when the periods of microphone malfunction occurred.

Chapter 6

Visualising the Soundscape using Acoustic Indices

The emphasis of this chapter is the visualisation of soundscapes across very-long temporal periods using acoustic indices. The six spectral and fourteen summary acoustic indices calculated in Chapter 4 were used to develop two new forms of visualisations.

6.1 OVERVIEW

This chapter is the first of two chapters that address objective 3, the provision of visualisation techniques for very-long-duration audio recordings. The two plots described in this chapter utilise the spectral or summary acoustic indices. They perform a preliminary role in data exploration of very-long-recordings. The ribbon plots introduced in Section 6.2 are designed to extend the number of days visualised at one time from one to many. The PCA diel plots described in Section 6.3 are easy to produce and provide a view into the structure of the data. The preparation of each plot is described before an interpretation of each plot is provided.

6.2 RIBBON PLOTS

Ribbon plots (Figure 6.3) were developed to visualise months of data and provide a means of examining the gradual daily changes in the audio data. A ribbon plot consists of ribbons stacked vertically to visualise many days of acoustic data.

A brief description of LDFC spectrograms precedes the description of the ribbon plots because to interpret the ribbon plots requires knowledge of how to interpret the LDFC spectrograms, see the captions of Figures 6.1 and 6.2. LDFC spectrograms (Towsey et al., 2014b) were developed to visualise hours of acoustic data. These images are produced by mapping three different spectral indices to the red, green, and blue (RGB) channels. They have a one-minute horizontal resolution and a vertical resolution dependent on the window length used in the FFT.

For sound events that significantly increase one of the spectral acoustic indices used in the LDFC spectrograms, the event will appear either red, green, or blue. Other colours indicate an increase in more than one acoustic index. For example, rain increases the Acoustic Complexity Index (ACI) (Depraetere et al., 2012), so rain appears red in the top LDFC spectrogram (see [1] in Figure 6.1). Short duration birdcalls increase the Temporal Entropy (ENT) index because the short period of their calls concentrates the acoustic energy temporally; this is why most birdcalls but not all, appear green. The Events per Second (EVN) index is increased by wind resulting in wind appearing blue (see [5] in Figure 6.2). Note, rain, birds, wind and orthoptera are best observed with the spectral acoustic indices (ACIsp-ENTsp-EVNsp) used in the top images. Cicadas are better observed in the bottom images using the BGNsp-POWsp-SPTsp spectral acoustic indices (see [3] and [4] in Figure 6.1). Also notice the absence of colour in the position corresponding to [3], the acoustic indices in the top image are not being increased by this species of cicada.

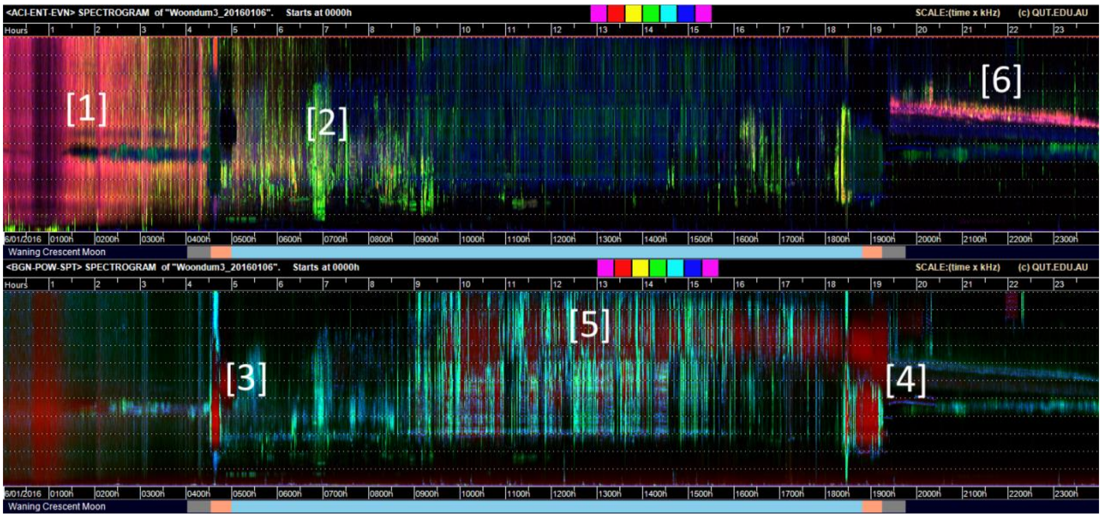


Figure 6.1 A LDFC spectrogram from 6 January 2016 at Woondum National Park. The top spectrogram displays ACIsp-ENTsp-EVNsp mapped to the RGB channels. The bottom spectrogram displays BGNsp-POWsp-SPTsp. Different combinations of acoustic indices show different events for the same 24-hour period. The broadband red in the top image is rain [1] occurring between midnight and 6:30 am. Birds [2] are calling after the rain. Cicadas are calling at dawn [3] and dusk [4], the dawn calling starts at 4:30 am and the dusk chorus starts at 6:30 pm. Cicadas are also calling for most of the daytime commencing around 9 am. The pink trail is Orthoptera [6] commencing around 7:30 pm.

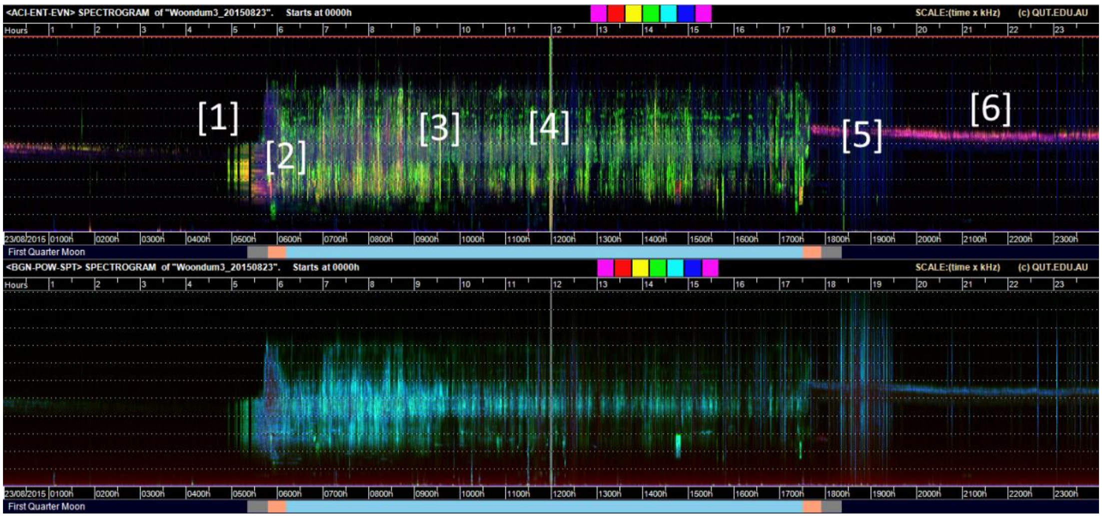


Figure 6.2 A LDFC spectrogram from 23 August 2016 at Woondum National Park. The Eastern Yellow Robin starts calling at 4:55 am, this is seen in yellow in the top spectrogram [1]. Other birds join the morning chorus at 5:25 am [2]. Bird calling continues throughout the day [3]. At 12 noon, the batteries were changed on the recorder which took 2 minutes [4]. Throughout the day there are some gusts of wind, between 6:15 pm and 7:30 pm the wind becomes more pronounced, this is seen as broadband blue in the top image [5]. At 5:42 pm the Orthoptera start calling (pink trail), this continues for the remainder of the night [6]. The spectral acoustic indices used correspond to those used in Figure 6.1.

Species can be identified in LDFC spectrograms if the animal has called for more than one minute (Towsey et al., 2015), although long loud calls such as the Laughing Kookaburra *(Dacelo novaeguineae)* chorus can be detected in these images. These images allow navigation on a 24-hour time-scale and have been used by ecologists to locate cryptic species (Towsey et al., 2018b). The remainder of this chapter covers the visualisations developed for this thesis.

6.2.1 The Preparation of Ribbon Plots

A ribbon plot (Figure 6.3) consists of a series of vertically compressed LDFC spectrograms known as ribbons. To produce a ribbon the vertical resolution of a LDFC spectrogram is reduced from 256 to 32 pixels by determining the maximum value within each group of eight spectral values (Phillips, Towsey & Roe, 2017). The horizontal resolution of the spectrogram remains unchanged.

Successive ribbons are arranged vertically to produce a ribbon plot. The vertical stacking allows the comparison of all days within a month, allowing progressive daily changes to be revealed and examined.

The individual ribbons are assembled into a ribbon plot. It is constructed using CSS (Cascading Style Sheets) code and displayed in HTML (Hypertext Markup Language) format. The HTML file displays the ribbon plots and allows the ribbon plot to be scrolled through to view the full sequence. Clicking on a ribbon displays the corresponding LDFC spectrogram. Alternatively, LaTeX (The LaTeX Project, 2018) can be used to assemble the ribbon plots.

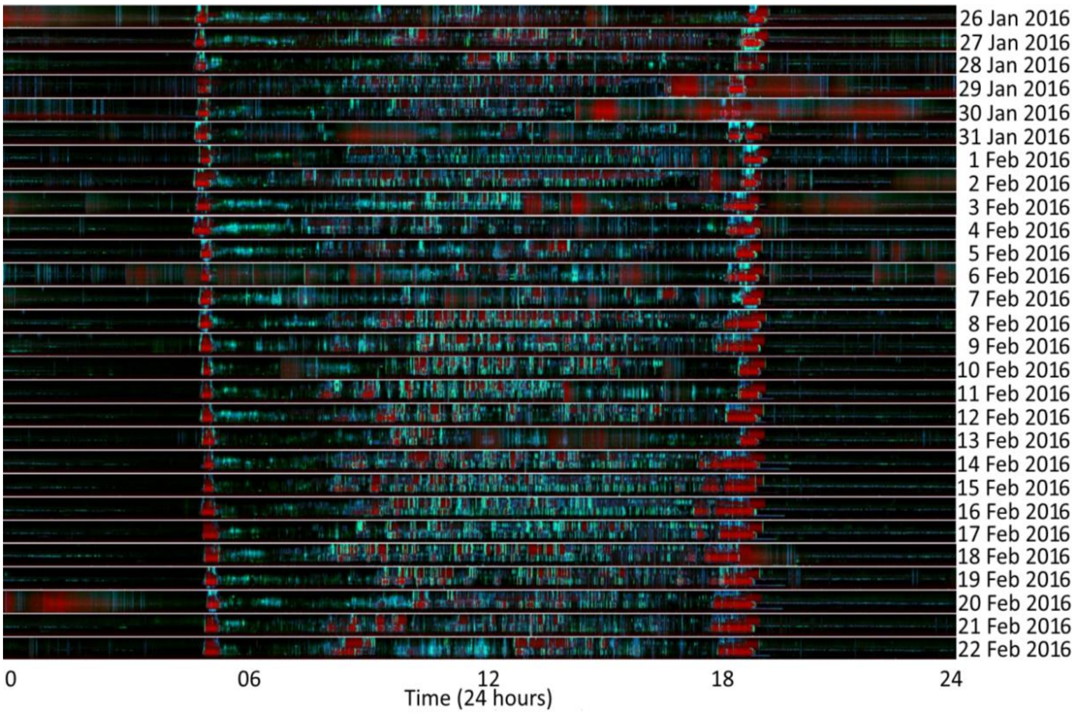


Figure 6.3 A ribbon plot showing the days from 26 January 2016 to 22 February 2016 from the Woondum National Park site using the spectral indices BGNsp-POWsp-SPTsp. The red in these images display the cicada choruses. Notice how the rain periods affect the calling of the cicadas during their dusk chorus on the 29 and 30 January 2016, shifting the chorus to an earlier time. In February 2016, the dusk cicada chorus is more prolonged than it had been during January 2016.

6.2.2 Interpretation of Ribbon Plots

The interpretation of the ribbon plots relies on knowledge of the patterns in LDFC spectrograms. This knowledge is gained by consultation with the original audio recordings. Once this knowledge is established, LDFC spectrograms from other recording sites can be interpreted with significant reductions in the time required to learn new patterns.

The blackness of the night is a consistent feature in most LDFC spectrograms denoting the quietness of the night. The bird morning choruses or the cicada choruses at dawn and dusk (Figure 6.3) orientate the viewer to the time and the position of sunrise and sunset.

The similarity in the appearance of patterns across sites is grounded in the psychological Gestalt theory (Myatt & Johnson, 2011, p.41) assisting in the rapid interpretation of the sound events displayed. The human eye readily detects small changes in patterns (Shneiderman, 1996) and the meaning of these patterns are quickly learned through listening to samples of audio. Ribbon plots are ideal for detecting slight daily changes.

Figure 6.3 shows the ribbon plot of the period from the 26 January 2016 to the 22nd February 2016 at the Woondum National Park site. The almost constant day length at the end of spring creates an almost vertical alignment of the morning and evening choruses. The red patches at dawn and dusk are cicada choruses, appearing more consistent at dusk. On the 29 and 30 January 2016, the cicada chorus shifts to an earlier time when compared to the other days. Listening to the recording for these days reveals the presence of thunderstorms. The storms appear to be disrupting the timing of the cicada chorus that is otherwise occurring consistently. Storms are known to affect the calling of the Australian Bladder Cicada (*Cystosoma saundersii*) (Doolan & Mac Nally, 1981). The detection of the occurrence of subtle changes such as this provides a better understanding of ecosystems and the associations between animal behaviour and abiotic factors.

6.3 PCA DIEL PLOTS (THIRTEEN MONTH DATASETS)

PCA diel plots (Figures 6.4 and 6.6) follow the earlier development of Extended Acoustic Summary (EASY) images (Towsey et al., 2014b). PCA diel plots map the first three principal components of PCA to the red, green, and blue channels respectively.

PCA diel plots have a horizontal resolution of 60 pixels per hour requiring 1440 pixels to span the 24-hour period from midnight to midnight. The vertical resolution is one pixel per day. Row 1 at the top of the image represents the first day and the last day at the bottom.

The advantage of using the first three PCA components over the use of three acoustic indices as in the case of EASY images (Towsey et al., 2014b) is the representation of more of the variance across the acoustic indices. Table 6.1 summarises the variance in the first three PCA coefficients from the twelve normalised summary acoustic indices in the thirteen-month dataset (Section 4.8.2). The total variance of the first three PCA coefficients is 65.4%.

Table 6.1 The standard deviation, variance and cumulative proportion of the total variance in the first three principal components of PCA calculated over the 13-month dataset (see Section 4.8.2).

	PC1	PC2	PC3
Standard deviation	0.5431	0.2738	0.24264
Proportion of variance	0.4500	0.1143	0.08982
Cumulative proportion	0.4500	0.5643	0.65418

6.3.1 The Preparation of PCA Diel plots

PCA diel plots (Figures 6.4 and 6.6) were produced using the thirteen-month dataset described in Chapter 4. The PCA components are calculated on the dataset of normalised acoustic indices using the R stats package (*prcomp* function) (R Core Team, 2016). The first three principal components are then scaled between 0 and 1 and multiplied by 255 to provide the necessary values to map to the RGB channels.

A second version of the PCA diel plots was produced (Figures 6.5 and 6.7) to cater for people with colour-blindness. To produce the plot, the first three PCA coefficients were clustered using k-means into eleven clusters. The clusters were mapped to a colour-blind pallet obtained from ColourBrewer2 (Brewer, Harrower & The Pennsylvania State University, 2017) using a diverging red, yellow, blue colour scheme and selecting 'colourblind safe' colours.

The *prcomp* function cannot accept NA values. The NA values in the dataset are kept to maintain the time-sequence integrity. To overcome this, the NA values are removed before the *prcomp* function is applied and reinserted afterward, as number 1. The reinsertion of the missing minutes restores the time-series integrity. The maximum value of 1, when mapped to the red, green, and blue channels will appear white to denote a missing minute.

6.3.2 The Interpretation of PCA Diel plots

PCA diel plots (Figures 6.4 and 6.6) bring order to the many hundreds of thousands of minutes. The twenty-four-hour diurnal cycle becomes clearly evident. These plots are explained by referring to the numbers on Figure 6.4. Figures 6.4 and 6.6 can be compared because the recording sites are only 25 kilometres apart, therefore a general correspondence of features can be expected.

In Figure 6.4, the dawn bird chorus [1] appears between civil-dawn and sunrise (the two curved dotted black lines to the left). Civil-dawn is the time when the sun is six degrees below the horizon. The cicadas that are calling at dusk between sunset and civil-sunset [2] appear green; they commence during the latter part of November 2015 and continue at least until the 1st February 2016. Cicadas are also calling during the day [3] and these cicada calls are displayed in bright green from late November 2015 to January 2016. The yellow patch [4] after civil sunset is particularly evident from September to November 2015, this is night-time calling insects presumably mostly orthoptera (crickets).

Rain [6] appears as dark blue horizontal streaks and, this is more prevalent at the Woondum National Park site. The patch of green before sunset in late September 2015 [5] corresponds to four days of thunderstorms on the 27, 28, 29 and 30 September 2015 at the Gympie National Park site. The deterioration of both microphones during the three-day period following heavy rainstorm [7] late on the 27th October 2015 is also evident.

The PCA diel plots show a correspondence of sound events across sites, although the Woondum National Park site (Figure 6.6) receives more rain than the Gympie National Park site. The insects calling at night occur at both sites but appear more distinct in Figure 6.4. The cicada dawn and dusk chorus start at the two recording sites at approximately the same time of year. However, the daytime cicada choruses appear to be more extensive at the Woondum National Park site.

6.4 SUMMARY

This chapter introduced two new visualisation techniques, the Ribbon plot, and the PCA diel plot. Ribbon plots facilitate the examination of gradual daily and broad seasonal changes in acoustic events by displaying multiple days at one time.

This display of multiple days facilitates the comparison of daily patterns allowing subtle differences to become evident across days. These images could be adapted to target a particular species by focusing in on a particular frequency band and could prove useful in locating the calls of otherwise cryptic species. Alternatively, PCA diel plots (Figures 6.4 to 6.7) display periods of greatest variance in the acoustic indices by plotting the first three PCA coefficients. These plots are fast to produce once the normalised dataset has been constructed. They provide an overview of areas of interest in the data thus providing a navigable map to assist in the preliminary exploration of the recording. This technique also highlights periods of time when microphone problems have occurred. These plots were adapted for people with colour-blindness by clustering the PCA coefficients and mapping the clusters to a colour-blind pallet.

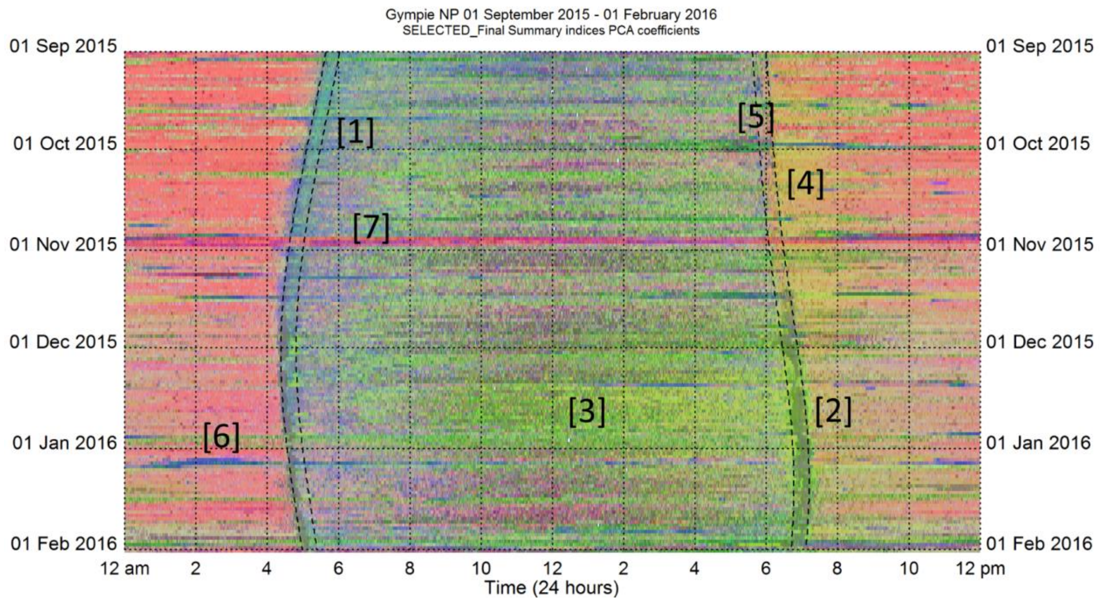


Figure 6.4 PCA Diel plot for Gympie National Park for 1 September 2015 to 1 February 2016 (five months) using the first three PCA coordinates assigned to the RGB channels of individual pixels. The four vertical dotted curved lines represent civil-dawn, sunrise, sunset and civil-dusk.

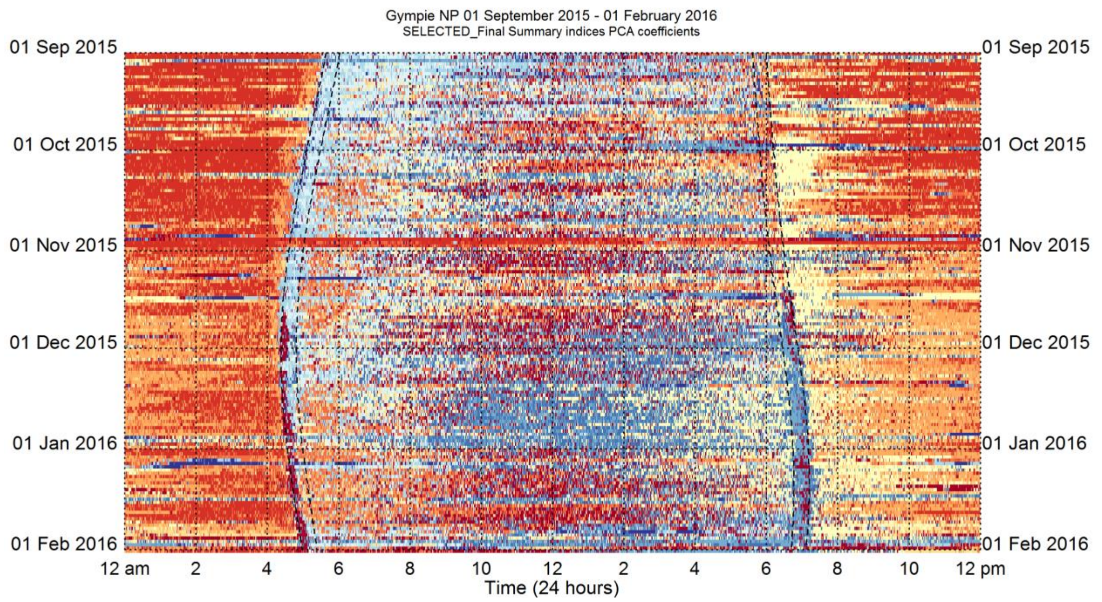


Figure 6.5 PCA Diel plot using colour-blind colours for the Gympie National Park site for 1 September 2015 to 1 February 2016 to represent clusters in the first three PCA coordinates. The use of discrete colours allows for an easier interpretation.

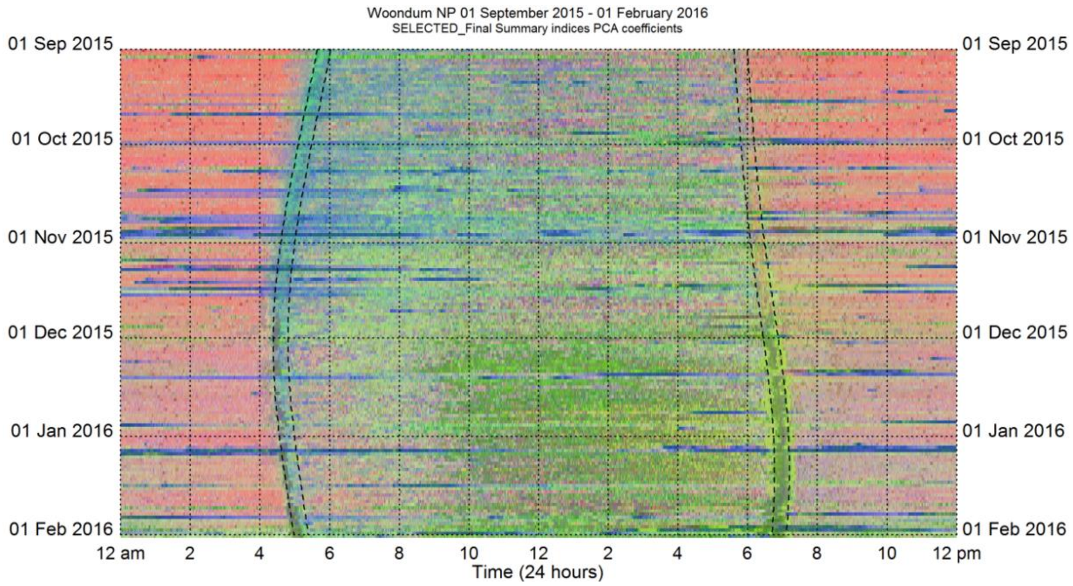


Figure 6.6 PCA Diel plot for Woondum National Park for 1 September 2015 to 1 February 2016 (five months) using the first three PCA coordinates assigned to the red, green, and blue channels. The four vertical dotted curved lines represent civil-dawn, sunrise, sunset and civil-dusk.

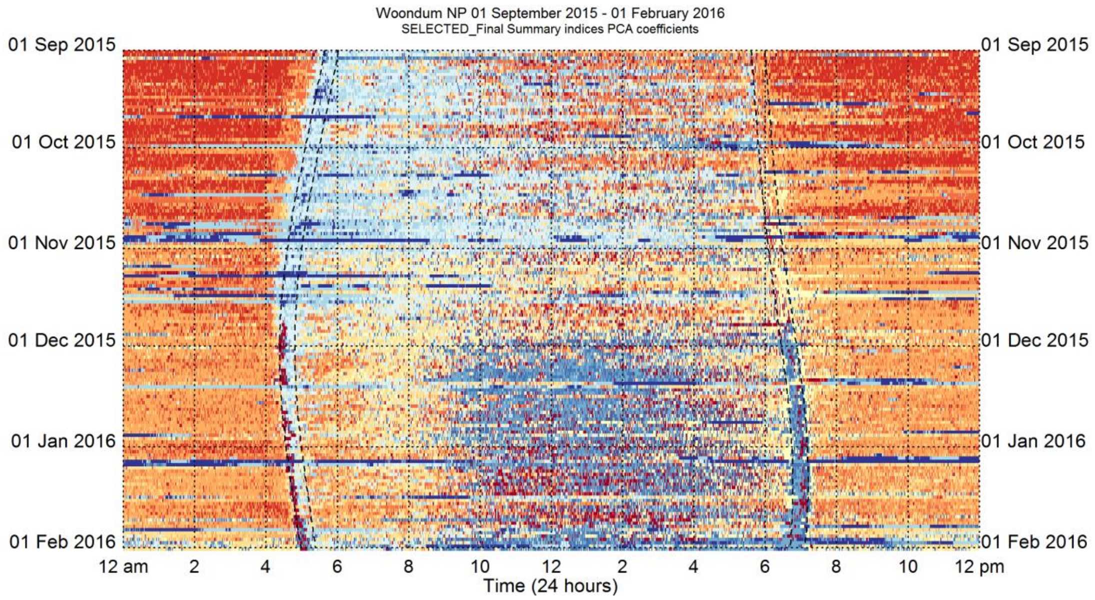


Figure 6.7 PCA Diel plot using colour-blind colours for the Woondum National Park site for 1 September 2015 to 1 February 2016 to represent clusters in the first three PCA coordinates. The use of discrete colours allows for an easier interpretation.

Chapter 7

The Selection of a Clustering Method

This chapter appraises four clustering methods in order to select a clustering method for the thirteen-month audio dataset. Previous clustering of soundscapes predominantly used hierarchical clustering (Rychtáriková & Vermeir, 2013; Torija et al., 2013; Yang & Kang, 2013); however, their choice was not explained. Because certain clustering methods are more suitable for particular datasets (Andreopoulos et al., 2008; Nguyen & Kwoh, 2015) a test was designed to find the optimum clustering method for an acoustic dataset.

7.1 OVERVIEW

In Chapter 1 (Section 1.4), clustering was proposed as the method of data reduction of the very-long-duration audio recordings because it is a proven unsupervised learning method. Additionally, hierarchical clustering and other clustering methods have been used previously on urban soundscapes showing a capacity to reveal the structure in these small datasets (Section 2.5.2). Clustering is therefore important to the achievement of objective 2. This chapter addresses objective 2, it explains the evaluation of four clustering methods, the criteria used, the results and the choice of the clustering method.

7.2 THE CLUSTERING METHODS

Four clustering methods, each representing one of the main types of clustering, were applied to the twelve-day dataset to choose a clustering method to be used on the thirteen-month dataset. The four algorithms are provided below.

7.2.1 Algorithm 1 Partitional Clustering

K-means clustering (kmeans, R ‘stats’ package (R Core Team, 2016)) with k values equal to 5, 10, 15, 20, 25, and 30. The k-means algorithm (see Section 2.5.2) clusters the twelve-day dataset into k clusters.

7.2.2 Algorithm 2 Hierarchical Clustering

Hierarchical clustering (*hclust,* R ‘stats’ package (R Core Team, 2016)) employing the average and Ward’s methods for evaluation. The resulting 17,280-leaf dendrogram was cut using the *cutree* function at heights of 5, 10, 15, 20, 25, and 30. Note: In the hclust function (Murtagh & Legendre, 2014) the ward.D2 method implements Ward’s algorithm (Ward, 1963).

7.2.3 Algorithm 3 Model-based Clustering

Use model-based clustering (*Mclust*, R ‘mclust’ package (Fraley, Raftery, Murphy & Scrucca, 2012)) to calculate the BIC for 1 to 50 clusters. This method as described in Section 2.5.2, determines the optimum cluster number (Fraley & Raftery, 2007), therefore producing a single cluster result.

7.2.4 Algorithm 4 Hybrid Clustering

The hybrid clustering method incorporates partition (k-means) and hierarchical clustering. It attempts to benefit from the features of both the k-means and the hierarchical clustering algorithms. The hybrid method is performed in three steps:

Step 1: Partition the data into a large number (k1) of clusters using k-means. For the twelve-day dataset, k1 values of 2000 to 4000 in steps of 500 were used.

Step 2: Use hierarchical clustering to cluster the k1 cluster centroids from step 1. Cut the tree using k2 values from ranging 10 to 100 in increments of 5.

Step 3: Assign each instance in the dataset to a k2 cluster (obtained from step 2) using k-nearest-neighbour (*knn*), R class package (Venables & Ripley, 2002).

7.3 THE EVALUATION OF THE CLUSTERING METHODS

Three criteria were used to evaluate the clustering algorithms. The clustering algorithms should:

1. Minimise the clustering error
2. Remain robust to small changes in the number of clusters (and other clustering parameters) and
3. Be able to scale to a large dataset.

Criteria 1 will evaluate how well the cluster result reflects the similarity and differences in the twelve days (Table 4.2) of audio data used to test the methods.

Criteria 2 relate to the stability of the error measure, the chosen method will remain stable over a range of parameters.

Criteria 3 is essential. The method must be useable on very large audio datasets.

7.4 OPTIMISATION OF THE CLUSTERING PARAMETERS

Algorithms 1 and 2 require the optimisation of the parameter k (cluster number). Algorithm 3 does not need optimisation because the BIC determines the optimum number of clusters. Algorithm 4 has two parameters k1 and k2 needing optimisation.

The optimum k value is normally determined by the quantisation error with measures such as the Silhouette Index (Rousseeuw, 1987) or Dunn Index (Dunn, 1974). The optimum value of k is expected to correspond with a drop in the quantisation error. In our case, an index to measure the distance between the four groups of three days in the twelve-day dataset was devised and used to optimise the clustering.

The four clustering algorithms (Section 7.2) were applied to the twelve-day dataset. The ability of a clustering method to separate the twelve days into four groups of three days (Table 4.2) became the measure of clustering “error” (Criteria 1). Sankupellay et al. (2015) used *twenty-four-hour acoustic signatures* to show the within-group similarity of consecutive days was greater than the between-group similarity of different sites. An *acoustic signature* is a frequency histogram of the count of each cluster within a 24-hour period.

The clustering should ideally produce clusters (and subsequent acoustic signatures) that divide the twelve days into four groups. The intra-three-day-distance (I3DD) error index was formulated to measure the extent to which the clustering departs from the ‘ideal’ clustering. The ideal is where the cluster result indicates a clear separation of the twelve days into the four groups of days in Table 4.2 due to expected site and seasonal differences.

The intra-three-day-distance (I3DD) error measure is reliant on two assumptions:

1. The biophonic content from vocalising species, is more similar in 24-hour rain-and-wind-free recordings if the recorded days are closer in time and space (distance between the recording sites). Conversely, the further apart two 24-hour recordings are seasonally and spatially, the more likely the divergence in the biophony.
2. The clustering result of 24-hour recordings with similar biophony will have more similar *acoustic signatures* (Sankupellay et al., 2015) than those of acoustically dissimilar 24-hour recordings.

The separation of the twelve days into four groups of three days was evaluated by clustering the acoustic signatures. Hierarchical clustering (using hclust in the R stats package (R Core Team, 2016), distance metric = ward.D2) of the acoustic signatures produced a 12-leaf dendrogram (see Figure 7.1).

The dendrograms were used to calculate the novel I3DD error measure. I3DD measures the total inter-group integrity, it is a measure of how far the dendrogram differs from the 'ideal'. An 'ideal' dendrogram would show the separation of the four groups of three days: days 1, 2, 3, days 4, 5, 6, days 7, 8, 9 and days 10, 11, 12 as per Table 4.2.

To calculate I3DD, average the maximum heights separating the pairs of group members. For example, in Figure 7.1, the I3DD value for days 7 to 9 is (145 + 101)/2 = 123. Repeat for the other three groups. For days 10 to 12, I3DD = (240 + 1378)/2 = 809, days 1 to 3, I3DD = (113 + 571)/2 = 342 and for days 4 to 6, I3DD = (316 + 737)/3 = 526.5. The sum of the four I3DD values is normalised by dividing by the height of the tree. The I3DD equals (123 + 809 + 342 + 526.5)/1378 = 1.306 for this clustering run. The I3DD value measures the extent to which the dendrogram departs from the "ideal" as described, in this sense it is an "error" measure. Smaller I3DD values are expected when the clusters have partitioned closer to the expected 'ideal'.

The minimisation of the quantisation 'error' (Criterion 1 – Section 7.3) is not the only criterion for choosing a clustering method. The method should also be insensitive to small changes in the parameter values (Criterion 2) and the method should scale to a large dataset (Criterion 3).

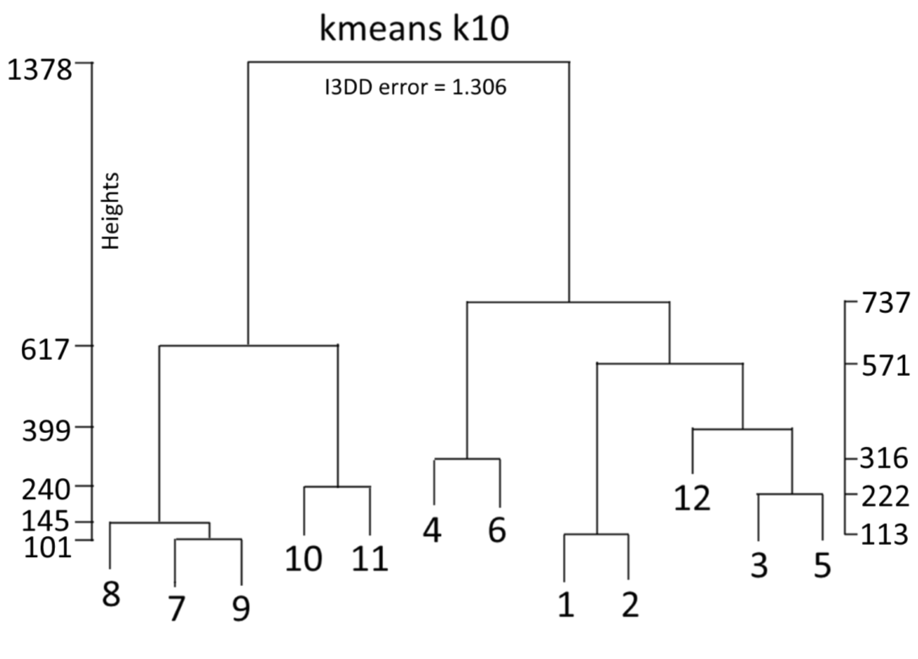


Figure 7.1 Dendrogram for k-means clustering of the twelve-day dataset (k=10).

7.5 THE CHOICE OF THE CLUSTERING METHOD

The I3DD ‘error’ curves (Figure 7.2a) indicate the optimum number of clusters for the 12-day dataset is within the range of 10 to 15 for Algorithms 1 (k-means) and Algorithm 2 (hierarchical-Ward). K-means achieved a lower error than either hierarchical methods.

Algorithm 3 (model-based clustering) produced a single result of 39 clusters with a complex ellipsoidal model with variable shaped clusters. The I3DD ‘error’ of 1.8 was high compared to the other clustering methods. Due to the high I3DD and long computation time (about 10 hours on a 16 GB RAM (Intel(R) Core(TM) i7-4600U CPU @ 2.1GHz, 2701 MHz, 2 Core(s), 4 Logical Processors), it was decided to remove this method from further consideration.

The lowest I3DD error (criteria 1) occurred for the k-means (Algorithm 1 – Figure 7.2a) and the hybrid (Algorithm 4 – Figure 7.2b) methods. The application of criteria 2, low sensitivity to small changes in cluster parameters indicates the hybrid method (Algorithm 4) maintains low I3DD error values over a broader range of k2 values ranging from 10 to 20 (Figure 7.2b). Consequently, the hybrid algorithm (Algorithm 4 – Section 7.2) was chosen for clustering the thirteen-month dataset.

7.6 SUMMARY

Of the four methods tested, the hybrid clustering method provided the best clustering according to the criteria. This method consists of the combination of k-means and hierarchical cluster and was designed to take advantage of the best features of each method and to overcome the unfavourable features of either method. The clustering was optimised using a new optimisation error measure I3DD designed to quantify the inherent differences in acoustic data across time and space.

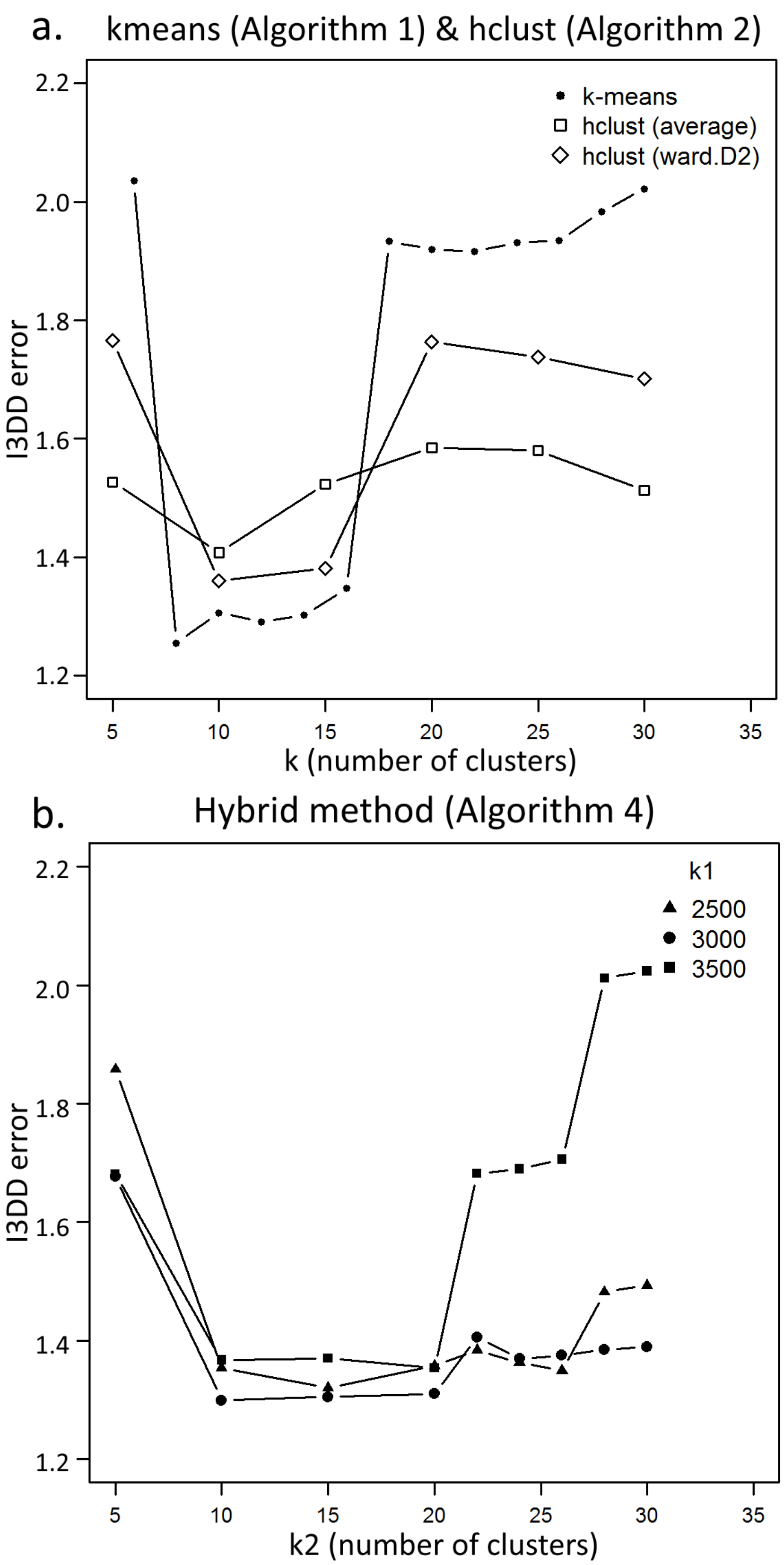


Figure 7.2 I3DD error curves for the clustering algorithms 1, 2, and 4. a. The I3DD error curves for the k-means and hierarchical clustering (*hclust)* of the 12-day dataset verses the values of k. b. The I3DD error curves for the hybrid clustering on the 12-day dataset verses different values of k1 and k2.

Chapter 8

Clustering and Cluster Interpretation

This chapter explains how the contents of the clusters were interpreted. This involved a combination of methods including listening to a sample of minutes, studying temporal distributions and false-colour visualisations, and an analysis of the cluster medoids. A cluster medoid is the cluster member that lies closest to the cluster centroid. Each of these methods is aimed at providing the evidence needed to apply a label to each cluster. Once a label has been applied to all clusters, an acoustic class sequence is established.

8.1 OVERVIEW

This chapter is structured in two sections; the first section describes the clustering of the thirteen-month dataset and the second the methods used to interpret the clusters.

8.2 CLUSTERING THE THIRTEEN-MONTH DATASET

The thirteen-month dataset from the two recording sites, inclusive of the 22nd s 2015 to the 23rd July 2016, was prepared as described in Chapter 4. The dataset was clustered using the hybrid clustering method (Section 7.2.4), the k1 values used in step 2 were 17500 to 27500 in steps of 2500.

The I3DD error measure (Section 7.4) was used to optimise the cluster result. The optimum number of clusters was 60 (see Figure 8.1a) corresponding to the k1 value of 25000 and k2 of 60. Sixty clusters were chosen because it corresponds to the lowest I3DD error. One of the dendrograms used in the clustering is provided in Figure 8.1b. Note the grouping of the three days within each of the four groups (refer to Table 4.2); day 12 is the only one that departs from its three-day group. It is believed that because day 12 (4 September 2015 at Woondum National Park) follows a day of rain and strong wind this disrupted the usual pattern of biophony making it different to Days 10 and 11.

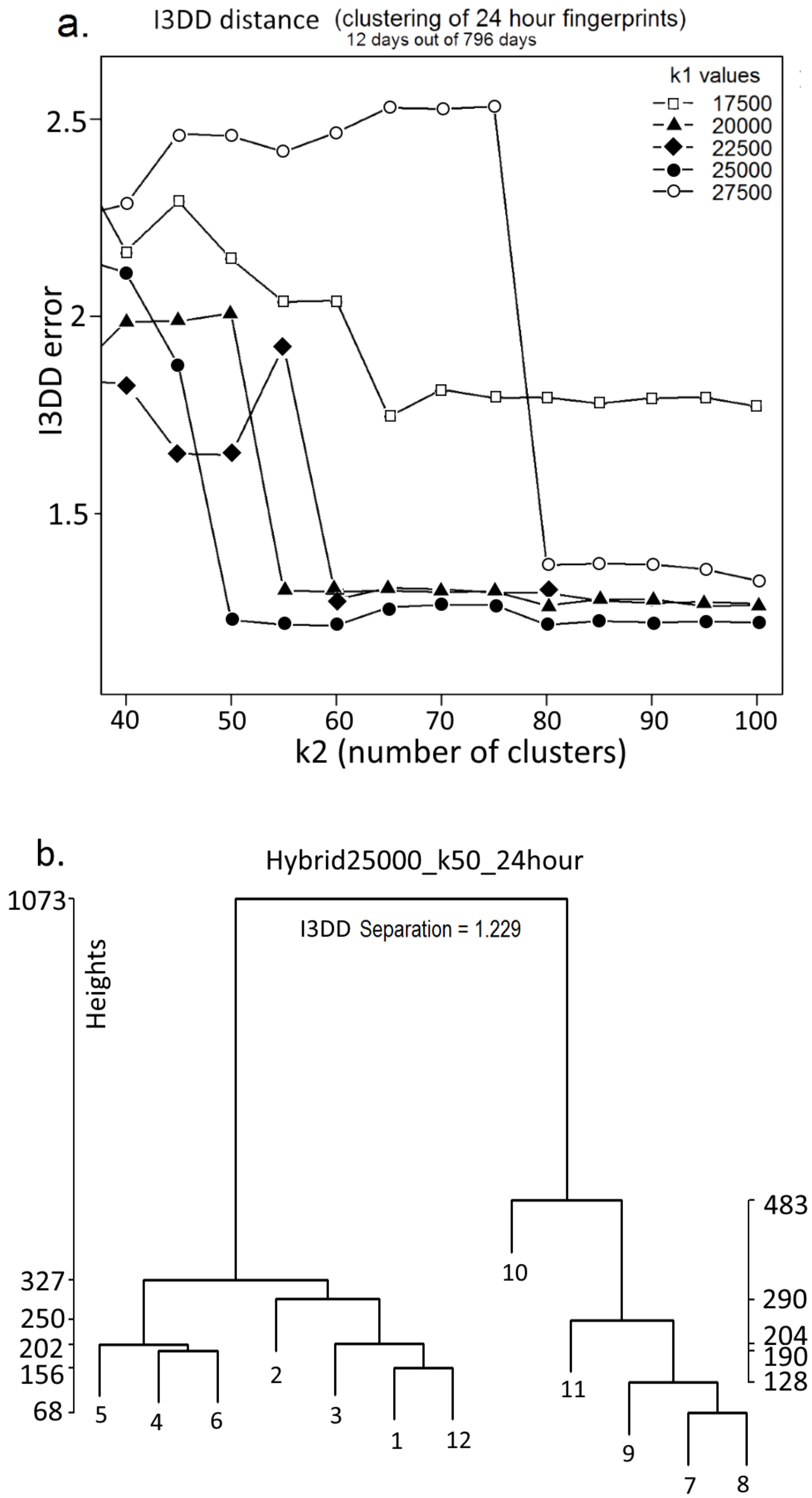


Figure 8.1a. The I3DD values verses the k1 and k2 hybrid clustering values. b. A dendrogram produced by the hierarchical clustering of the acoustic signatures of the twelve days (Phillips et al., 2018). https://doi.org/10.1371/journal.pone.0193345.g003

8.3 THE INTERPRETATION OF THE CLUSTER CONTENTS (THIRTEEN-MONTH DATASET)

Cluster content was interpreted using five methods.

1. Listening to a 20-minute sample from each cluster, a 10 minute sample from each of the two recording sites.
2. Examining composite false-colour spectrograms (Figures 8.2 to 8.6).
3. Inspecting the time-distribution of each cluster (Figures 8.7 to 8.11).
4. Studying the Sammon projection of the cluster medoids (Figures 8.12).
5. Examining the Radar plot of each cluster medoid (Figures 8.14 and 8.15).

8.3.1 Listening to a Sample from each Cluster

Listening to 20 one-minute randomly selected minutes from each cluster allowed an initial description of the cluster contents. This revealed six dominant sound sources: rain, wind, birds, orthoptera, aircraft, and cicadas. The Ecosounds website (Truskinger et al., 2014) was used to listen to a randomly selected 20 minute sample from each cluster. The table containing the summary of the dominant acoustic classes in the sampled minutes is available as supplementary information in Phillips et al. (2018), the hyperlink to this document is listed in Appendix A. Dominant sound sources were defined as the sound that could be heard most consistently in the minute. An absence of a dominant sound source was interpreted as ‘quiet’, the seventh acoustic class used. If 85% or more of the 20-minute sample consisted of one dominant acoustic class then the cluster was labelled with this class. Appendix D contains a summary of the acoustic class of each cluster. Mazaris et al. (2009) similarly classified audio into seven classes. They had only one class for wildlife and additional categories for sounds related to the sea and agriculture, however the other classes were similar.

8.3.2 Examining the Composite False-Colour Spectrograms

Composite false-colour spectrograms (Figures 8.2 to 8.6) are prepared by randomly selecting 600 minutes from each cluster and concatenating the one-minute false-colour spectrograms of these minutes. To interpret the composite false-colour spectrograms to determine the contents of each cluster, we rely on our ability to recall previously learned visual patterns, a trait well developed in humans (Shneiderman, 1996; Taboada-Crispi, Sahli, Orozco-Monteagudo, Hernández-Pacheco & Falcón-Ruiz, 2009, p.432). Listening either reinforces or corrects our previous understanding of the patterns by a process of categorisation and refinement (Gabora, Rosch & Aerts, 2008; Mennis, Peuquet & Qian, 2000).

The colours of the composite-false colour spectrograms (Figures 8.2 to 8.6) indicate the cluster contents. With previous experience of interpreting the LDFC spectrograms, the contents can be determined, for example, red indicates periods of moderate to heavy rain (see Figure 6.1). In general, broadband blue is wind, green in the mid-frequency range is birds, and trails of pink or blue are orthopterans. One or two examples from each of the seven acoustic classes are provided (Figures 8.2 to 8.6).

Each of the composite false-colour spectrograms match the expected colours for the class assigned to these clusters while listening to the 20 minute samples of these clusters. The composite false-colour spectrograms provide a large sample (10 hours) compared to the 20 minutes of listening, building the evidence for the verification of the cluster contents.

Figure 8.2 shows the composite false-colour spectrograms of two bird clusters (a & b) and two Orthopteran clusters (c & d). The green in the mid-frequency band indicates birds and the pink or blue orthopteran calls. The pink and blue specks do not form trails as they do in the LDFC spectrograms as in Figure 6.1. This is because the frequency of the orthopteran calls vary in response to temperature (Walker, 1962). The temperature changes through the night and these images reflect the random selection of minutes.

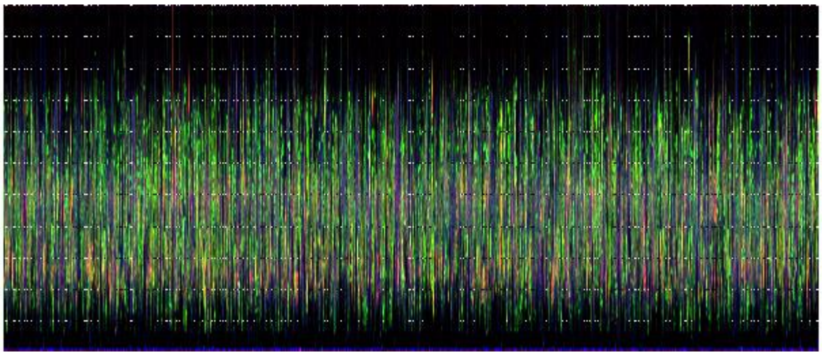
Figures 8.3 to 8.6 show two images for each cluster unlike Figure 8.2 which only showed one. The top image are formed from the spectral acoustic indices ACIsp-ENTsp-EVNsp and the bottom image from the spectral acoustic indices BGNsp-POWsp-SPTsp mapped to the RGB channels. The two images are provided because a more detailed interpretation can be made with both images.

Figure 8.3 shows two moderate rain clusters (clusters 59 and 18). The minutes contained in these clusters have high ACIsp values indicated by the red in the top images. The green in the lower frequencies in the top images indicates higher ENTsp values associated with short, sharp sounds. Cluster 18 may be detecting a greater number of individual raindrops compared to cluster 59. The BGNsp (red in the bottom images) is greater in Cluster 18 than Cluster 59. The rain intensity can also affect the frequency distribution of the sound (Bedoya, Isaza, Daza & López, 2017).

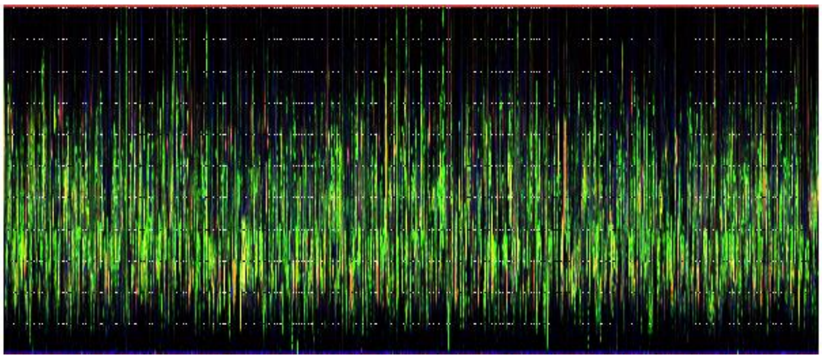
Figure 8.4 shows two strong wind clusters (clusters 42 and 47). The minutes contained in these clusters have high EVNsp values indicated by the blue in the top images. BGNsp is reasonably high in both clusters (red in bottom images) and the SPTsp acoustic index is elevated in cluster 42.

Figure 8.5 shows two contrasting clusters, cluster 41, a very quiet cluster and Cluster 49, an aircraft cluster. The very quiet cluster has an absence of colour, all acoustic indices have very low values which are lower than the threshold used in these images. This cluster occurred mostly at the Gympie National Park site and occupied 0.48% of the total minutes (91 hours 40 minutes). The aircraft cluster, cluster 49 has high EVN (blue in the top image) values and SPT (blue in the bottom image) values in the low frequencies (0–3 kHz).

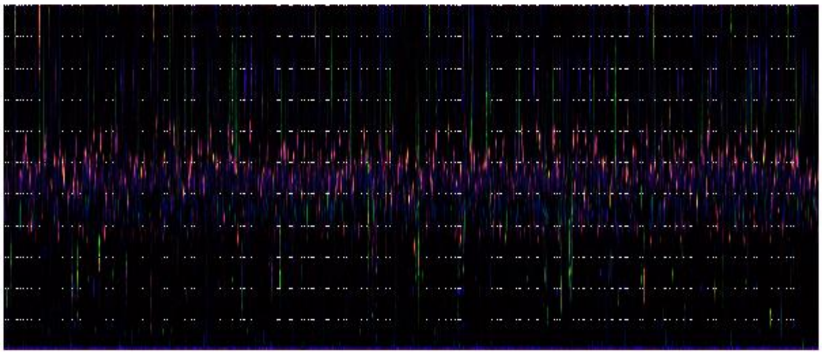
Figure 8.6 shows two cicada clusters, clusters 44 and 48. BGNsp (red in the bottom image) is high in Cluster 44 in the frequency range of 2–9 kHz. Cluster 48 appears different; the cluster contents have increased BGNsp values (red in the bottom image) and the SPT values above 2 kHz (blue in the bottom image). Cluster 44 mostly occurs at dawn and dusk (Figure 8.8) and Cluster 48 occurs mostly during the afternoon. Many of the daytime cicadas in cluster 48 contain the call of the Bark Squeaker Cicada (*Pauropsalta corticinus*), or other cicada species including the Black Tree-ticker (*Birrima varians*) or Phantom Knight Cicada (*Psaltoda brachypennis*) – see Appendix B for a link to the call of these species.



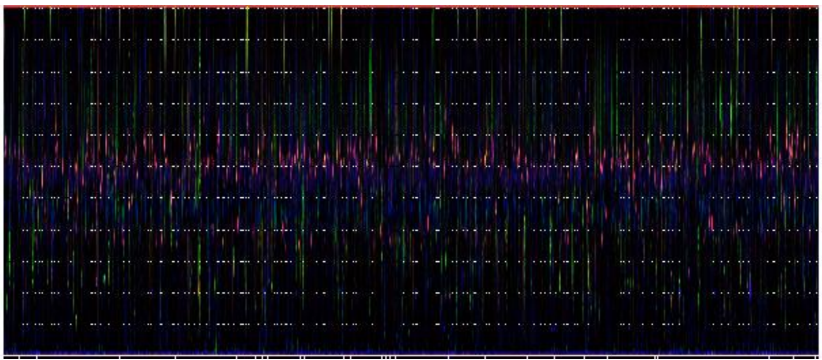
a. BIRDS (BIOPHONY) – CLUSTER 37



b. BIRDS (BIOPHONY) – CLUSTER 3

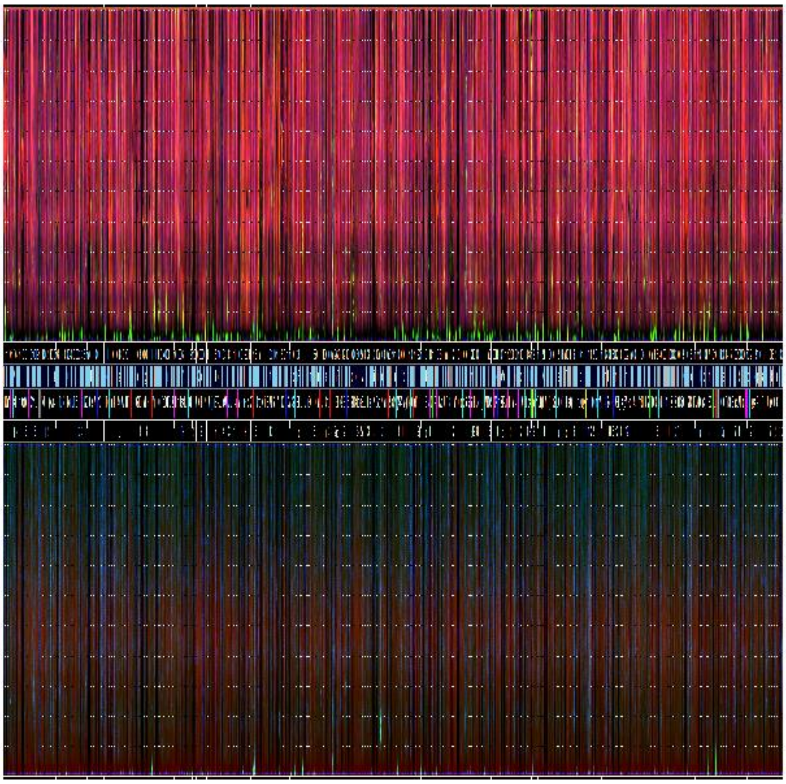


c. ORTHOPTERANS (BIOPHONY) – CLUSTER 29

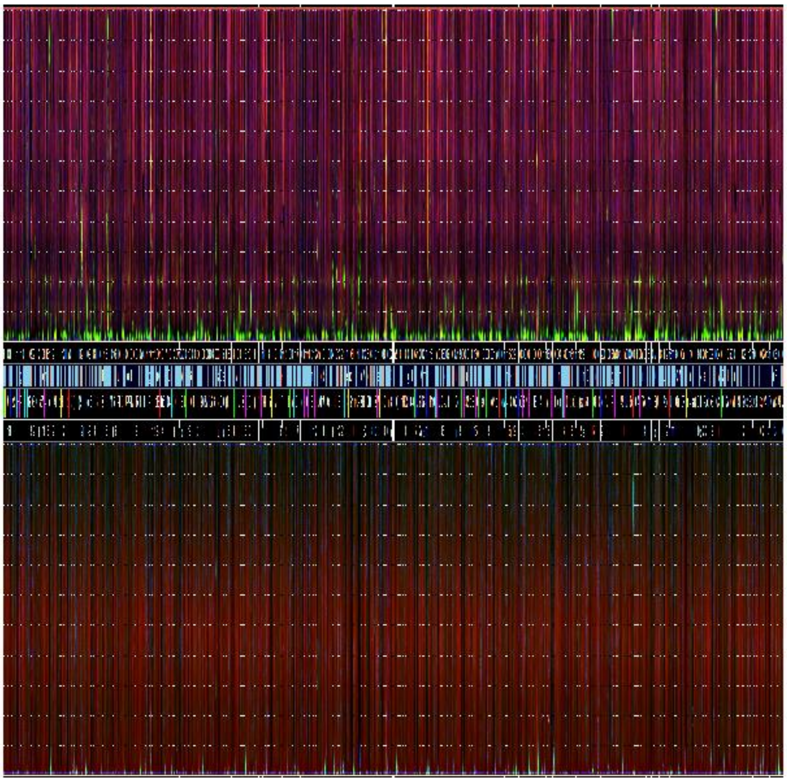


d. ORTHOPTERANS (BIOPHONY) – CLUSTER 1

Figure 8.2 Composite false-colour spectrograms of four clusters. a. Cluster 37 birds; b. Cluster 3 birds; c. Cluster 29 orthopterans; d. Cluster 1 orthopterans. Cluster 29 and Cluster 1 have very little colour apart from pink from the orthopteran calls, this indicates very consistent clusters. The frequency range of all images spans 0 to 11 kHz. The acoustic indices used were ACIsp-ENTsp-EVNsp.

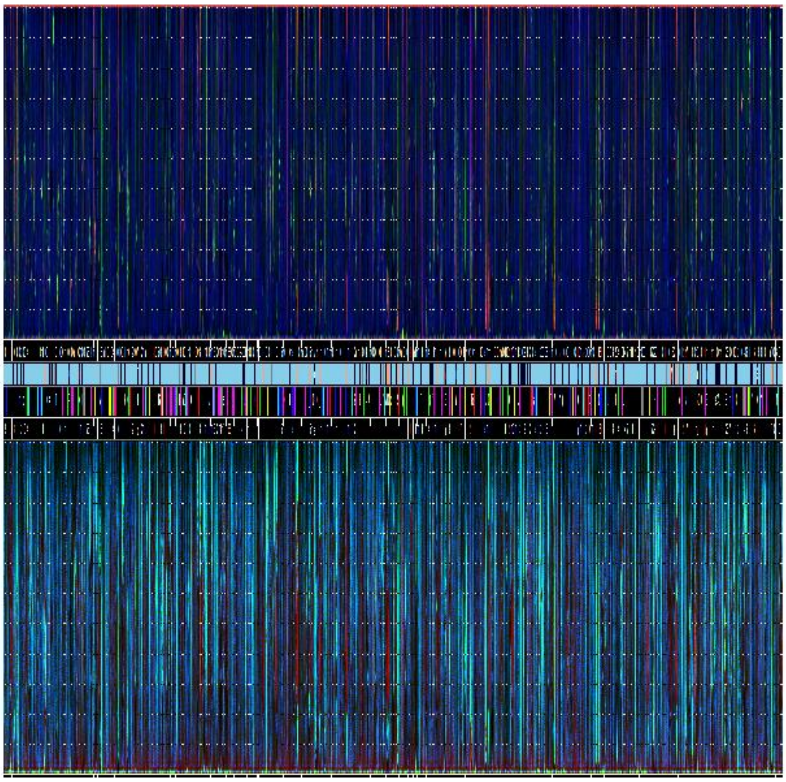


a. MODERATE RAIN (GEOPHONY) – CLUSTER 59

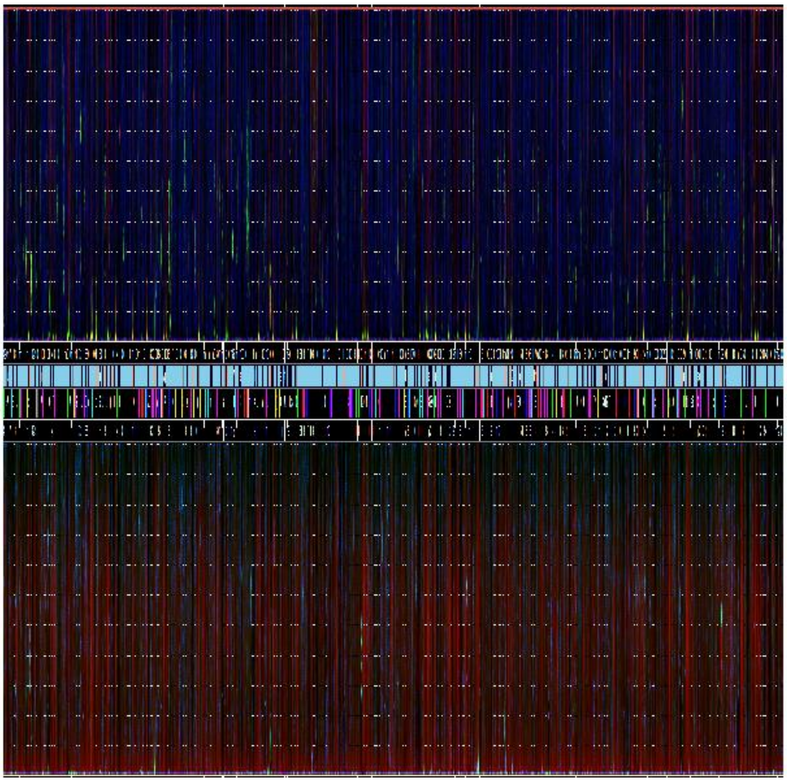


b. MODERATE RAIN (GEOPHONY) – CLUSTER 18

Figure 8.3: Composite false-colour spectrograms of a. Cluster 59 and b. Cluster 18, both moderate rain clusters. Unlike the images in Figure 8.2, these images consist of two images, a top and bottom spectral image. The acoustic indices used were ACIsp-ENTsp-EVNsp (top) and BGNsp-POWsp-SPTsp (bottom). BGNsp (red in the bottom image) is greater in Cluster 18. The frequency range of each component image is 0 to 11 kHz.

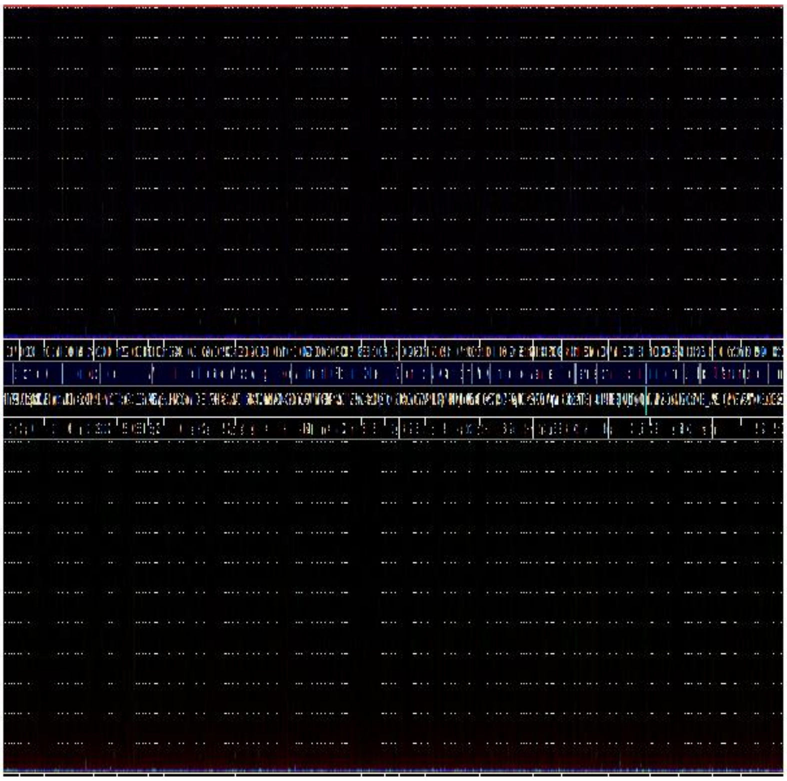


b. STRONG WIND (GEOPHONY) – CLUSTER 42

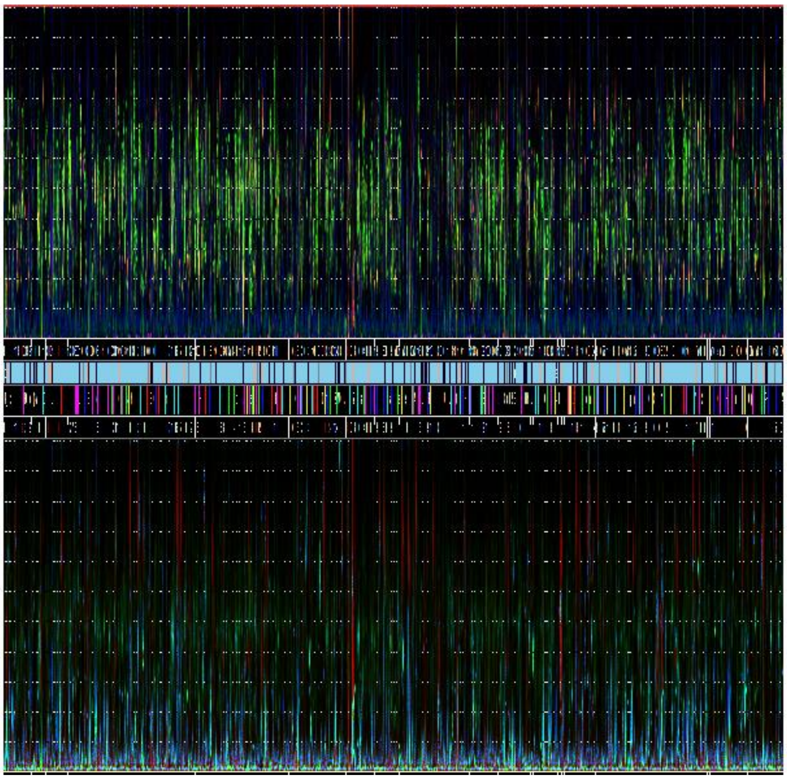


b. VERY STRONG WIND (GEOPHONY) – CLUSTER 47

Figure 8.4 Composite false-colour spectrograms of a. Cluster 42 and b. Cluster 47, both strong wind clusters. The acoustic indices used were ACIsp-ENTsp-EVNsp (top) and BGNsp-POWsp-SPTsp (bottom). Blue in the top image indicates the wind increases the EVNsp acoustic index, less so for the Cluster 47. SPTsp is higher in Cluster 42 and BGNsp is reasonably high in both clusters.

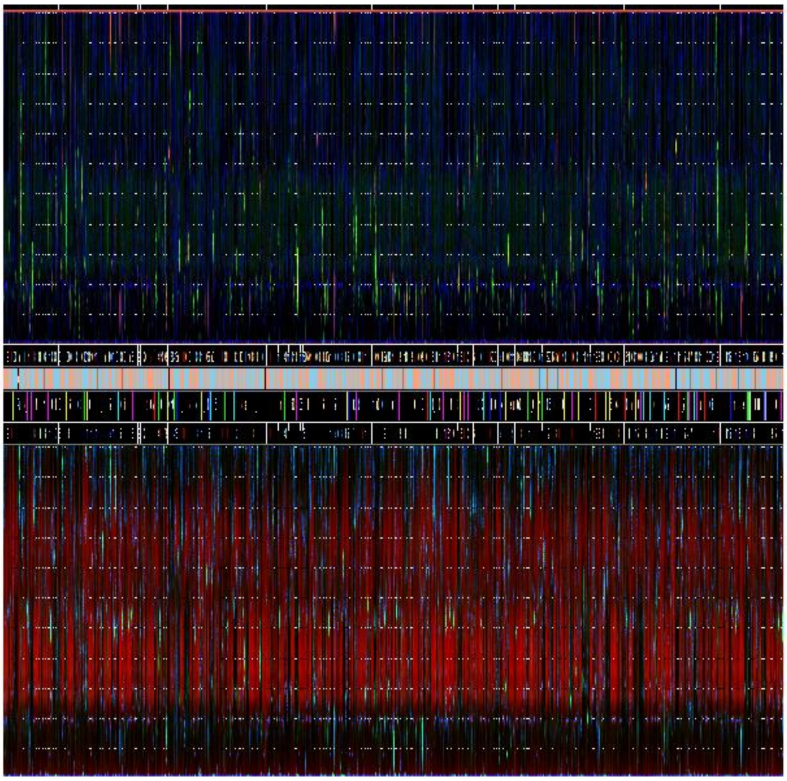


c. VERY QUIET – CLUSTER 41

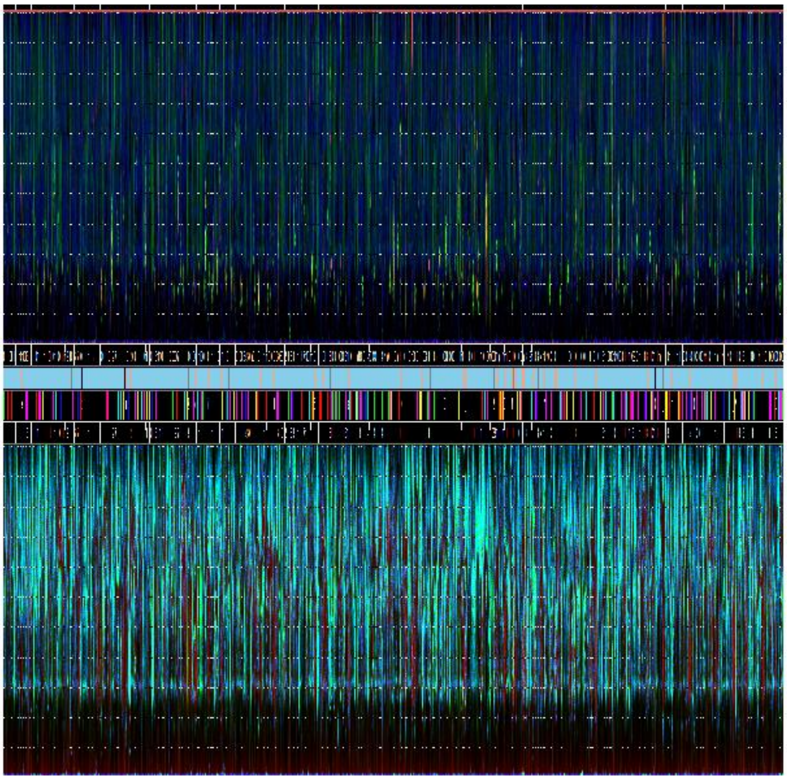


b. AIRCRAFT (ANTHROPOPHONY) – CLUSTER 49

Figure 8.5: Composite false-colour spectrograms of a. Cluster 41 a Very Quiet cluster and b. Cluster 49 an Aircraft cluster. The acoustic indices used were ACIsp-ENTsp-EVNsp (top) and BGNsp-POWsp-SPTsp (bottom). The very quiet cluster has an absence of colours indicating very little sound. The blue in the top image (EVNsp) and bottom image (SPTsp) in the < 3 kHz range is due to aircraft or thunder.



a. CICADAS (BIOPHONY) – CLUSTER 44



b. CICADAS (BIOPHONY) – CLUSTER 48

Figure 8.6a and b: Composite false-colour spectrograms of Cluster 44 and Cluster 48 Cicadas. The acoustic indices used ACIsp-ENTsp-EVNsp (top) and BGNsp-POWsp-SPTsp (bottom). The small amount of green in the top image indicates some birds. Red (in the bottom image) indicate high BGNsp in Cluster 44 particularly in 2-5 kHz range. The green and blue in Cluster 48 indicates high POWsp and SPTsp values.

8.3.3 Inspecting the Temporal-Distributions of each Cluster

The examination of the temporal distribution of clusters (Figures 8.7 to 8.11) provides further evidence for cluster interpretation. The diurnal patterns of the calls of birds, insects and frogs are well known, for example, birds call during the morning and day, orthopterans call at night (Pijanowski et al., 2011a; Ulloa et al., 2016). A diurnal pattern is not expected for rain clusters but wind clusters may have increased occurrence during the afternoon (Wiley & Richards, 1982, p.147 & 162).

Figure 8.7 shows the temporal distribution of cluster 37 a bird 'morning chorus' cluster at the Gympie National Park (top) and Woondum National Park site (bottom). The morning chorus cluster commences before sunrise peaking during the morning. This cluster peaks during spring in the months of August, September, and October 2015.

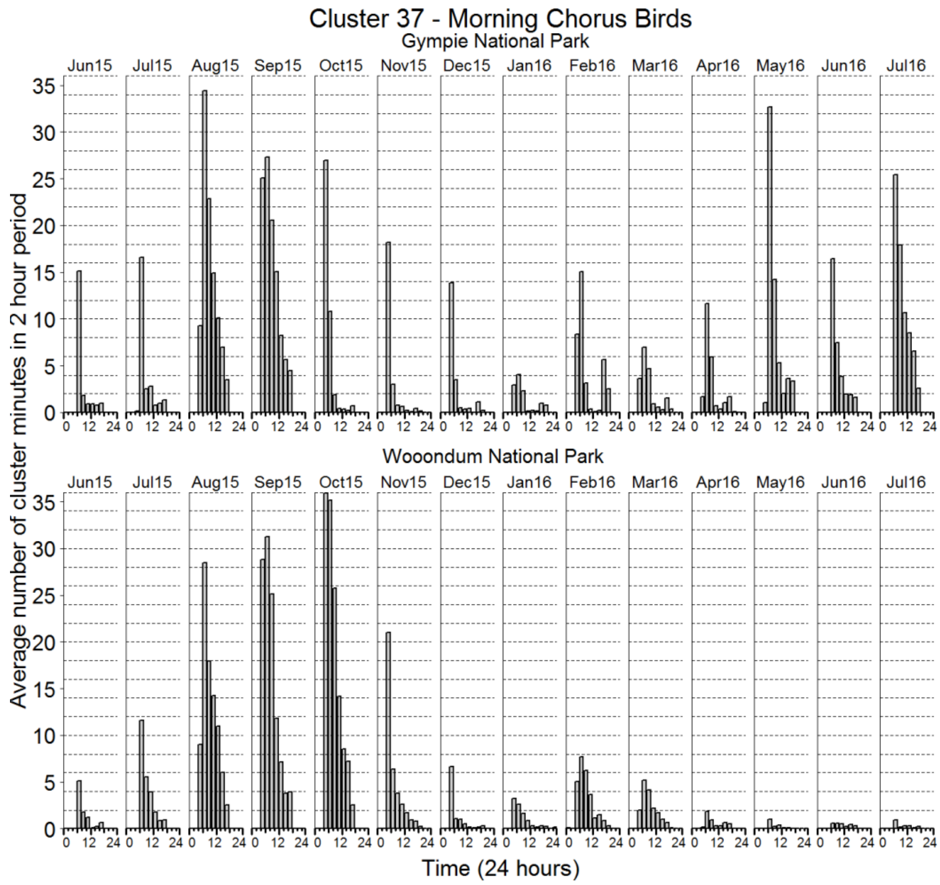


Figure 8.7 The temporal distribution of Cluster 37 a bird 'morning chorus' cluster. These plots show the average number of minutes in each cluster within two-hour periods across the months at the Gympie and Woondum National Park sites. At each site cluster 37 occurs mostly during the dawn period during spring (August to October 2015).

Figure 8.8 shows the temporal distribution of cluster 44, a dawn and dusk cicada cluster at the two recording sites. This dawn and dusk cicada cluster peaks during dawn and dusk during summer.

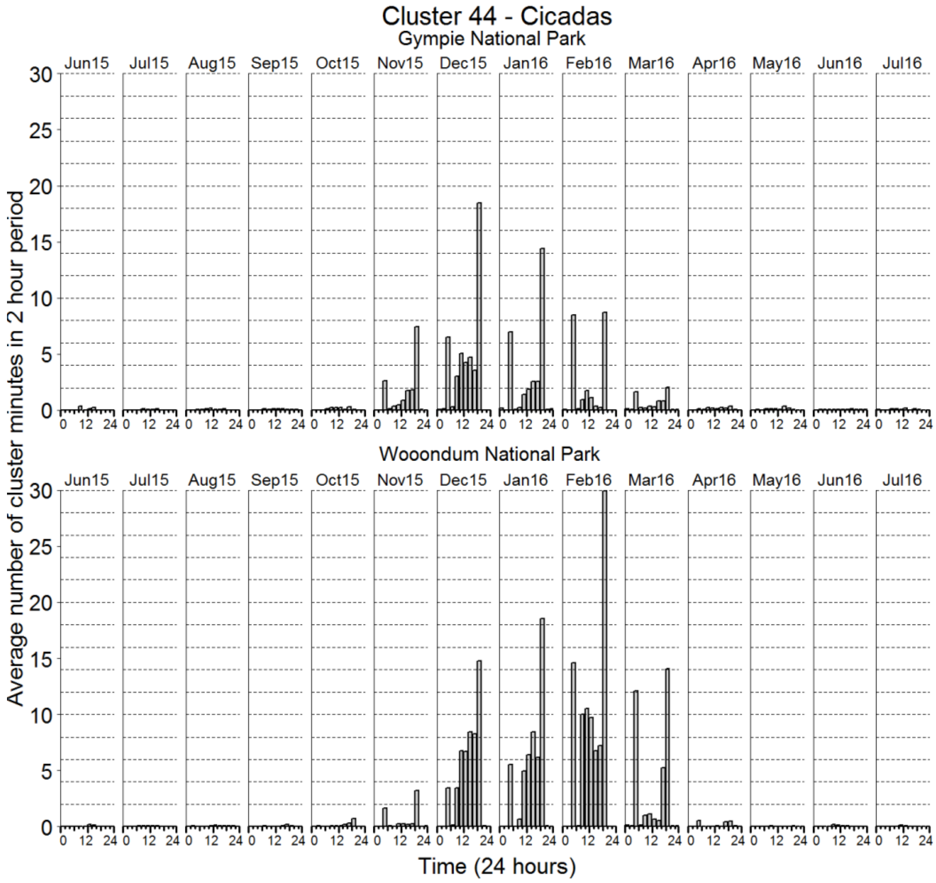


Figure 8.8 The temporal distribution of Cluster 44, a cicada cluster. These plots show the average number of minutes in each cluster within two-hour periods across the months at the Gympie and Woondum National Park sites. The cicadas in Cluster 44 dominate the dusk period from November 2015 to March 2016.

Figure 8.9 shows the temporal distributions of cluster 1 (top) orthopterans and cluster 41 (bottom) a very quiet cluster. The orthopteran cluster peaks after sunrise (between 8 and 10 pm) from November 2015 to March 2016. The quiet cluster also occupies a similar time of the night, but it occurs during winter. The soundscape during summer nights is dominated by orthopterans reducing the incidence of the quiet clusters during this season.

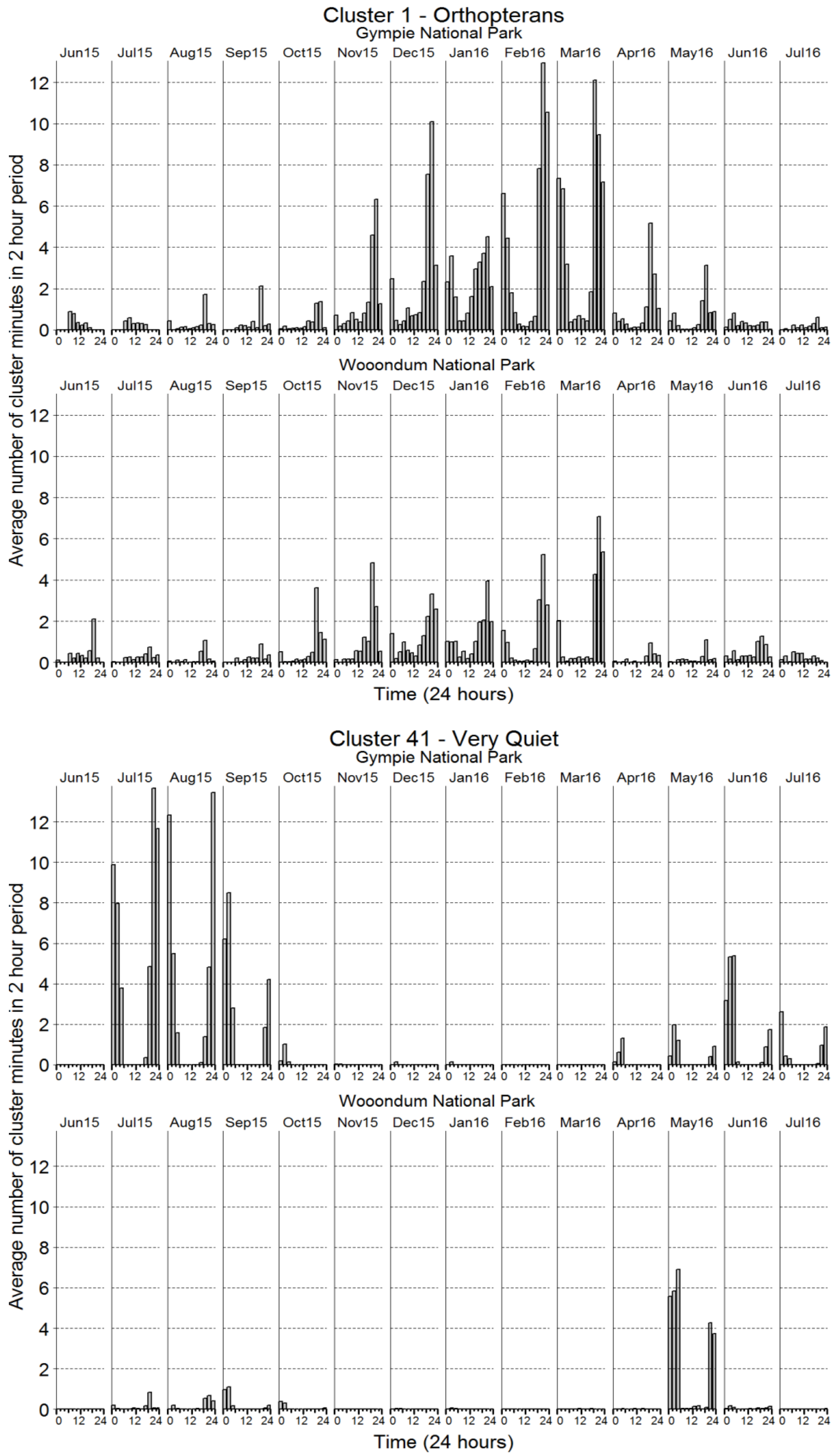


Figure 8.9 The temporal distribution of Cluster 1 orthopterans (top two plots) and Cluster 41 very quiet cluster (bottom two plots). These plots show the average number of minutes in each cluster within two-hour periods across the months at the Gympie and Woondum National Park sites. The orthopterans call during the night from October 2015 to May 2016. The very quiet cluster occurs at night during winter (July and August 2015).

Figure 8.10 shows the temporal distribution of two relatively small clusters cluster 49, an aircraft cluster (top), and clusters 42, a strong wind cluster (bottom). Both clusters occur during the day. An unusual peak in the aircraft cluster between 2 am to 4 am during November 2015 (marked with an arrow on Figure 8.10) was not due to the sound of an aircraft. It was due to thunder. A thunderstorm occurred on November 8, 2015. The grouping of thunder into the aircraft cluster is not surprising because the sound of rumbling thunder is similar to that of an overhead aircraft.

Rose plots (Figure 8.11) allow a more fine-scaled examination of the temporal distribution. Figure 8.11 shows the temporal distribution of the bird cluster 37 from August 2015 to December 2015. The timing of the cluster shifts in relation to sunrise occurring at increasingly earlier times throughout spring. During August 2015, the predominant timing of this cluster was between 6:00 and 6:30 am; by September 2015, this had changed to 5:30 to 6:00 am. These plots also indicate a peak of this bird cluster in late winter and a gradual decline from August to December 2015. The prevalence of this cluster during the dawn period led to the identification of cluster 37 as a “morning chorus” cluster.

The rose plots are also provided for two cicada clusters, clusters 44 and 48 (Figure 8.11). Cluster 44 occurs predominantly during dawn and dusk. Cluster 48 occurs mostly during the day between the hours of 10 am and 2 pm. The existence of patterns in these plots indicates an ecologically meaningful clustering result.

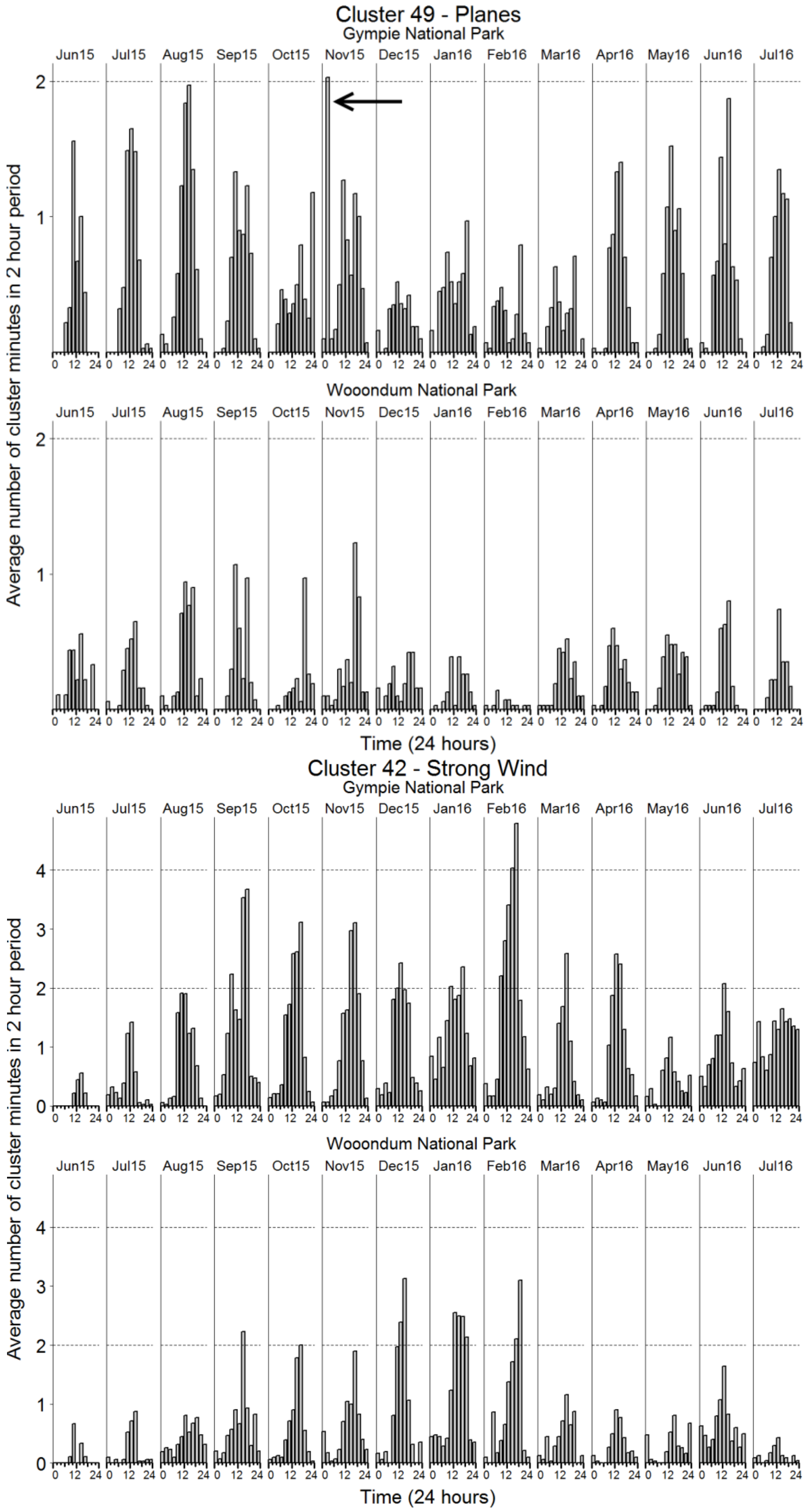


Figure 8.10 The temporal distribution of Cluster 49 aircraft (top two plots) and Cluster 42 a strong wind cluster (bottom two plots). These plots show the average number of minutes in each cluster within two-hour periods across the months at the Gympie and Woondum National Park sites. The aircraft cluster is occurring during the day in very low average number of minutes. The strong wind cluster also has a low average across each 2-hour period, with a definite temporal preference for the afternoon.

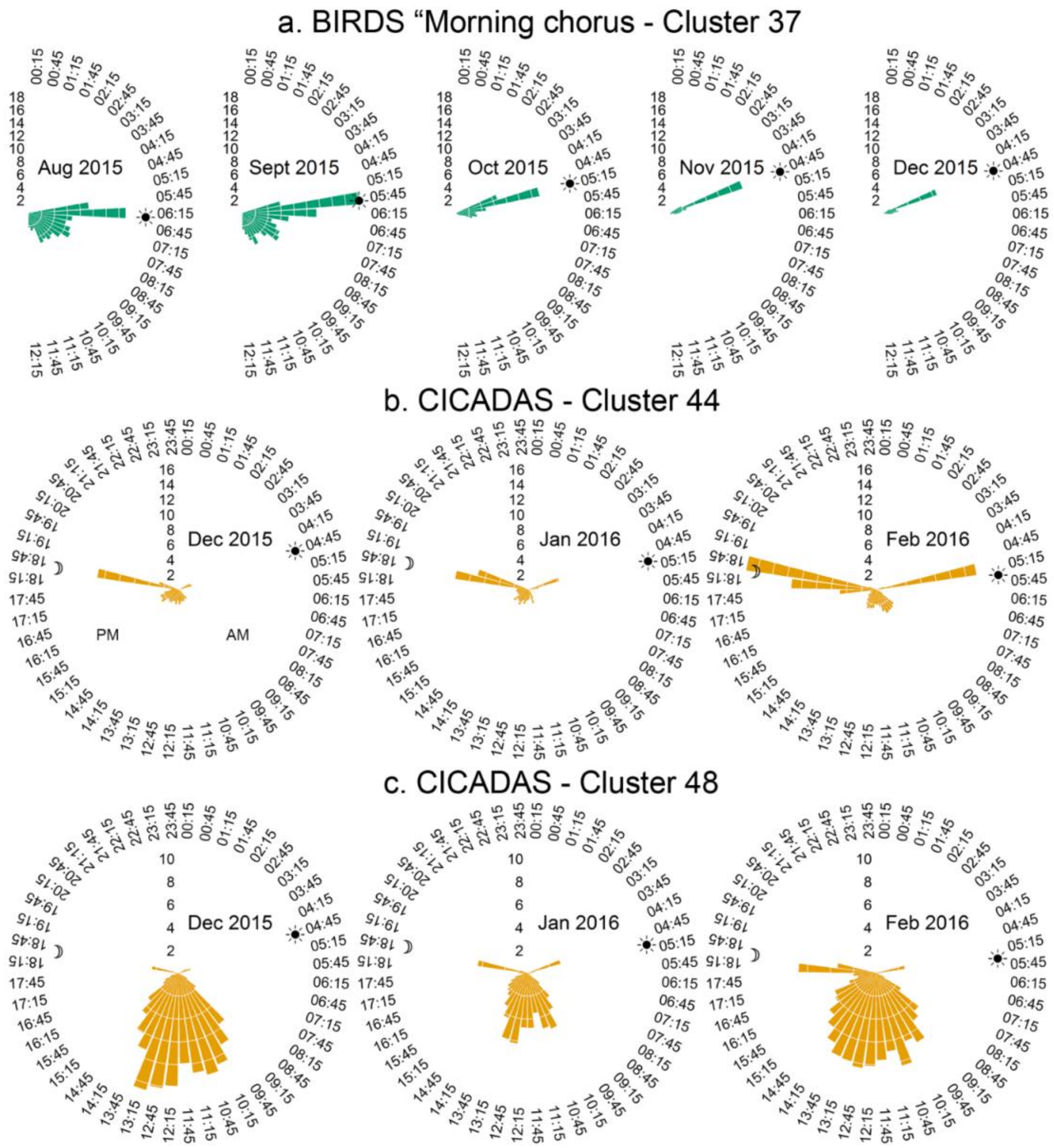


Figure 8.11: Rose plots of three clusters. a. Cluster 37, the 'morning chorus' cluster. b. Cluster 44 the 'dawn and dusk cicada' cluster and c. Cluster 48, the daytime cicadas. Image source: (Phillips et al., 2018) doi:https://doi.org/10.1371/journal.pone.0193345.g005

8.3.4 Studying the Sammon Projections of the Cluster Medoids

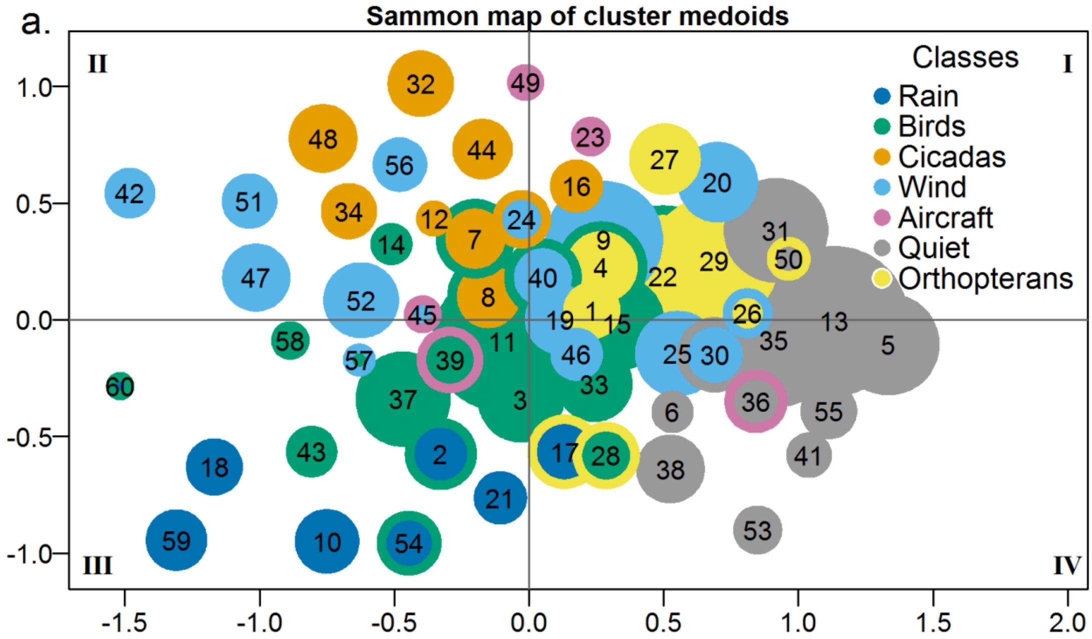
The medoids of the sixty clusters are projected in two dimensions to produce a Sammon map (Sammon, 1969). A Sammon map projects data onto a lower dimension while preserving the relative distances between the data points. A Sammon map was chosen instead of other dimensional reduction techniques such as PCA (Pearson, 1901) and t-SNE (van der Maaten & Hinton, 2008) because it minimises the difference between the inter-medoid distances and the projected distances. This is achieved by minimising a *stress* *function*, which compares the inter-point distances in the higher dimensional space to the distances in the projected space (Mesentean, Fischer & Smith, 2006; Sammon, 1969).

Figures 8.12a and b uses the Sammon function in the R package MASS (Venables & Ripley, 2002). In Figure 8.12a, the radii of the circles are scaled to the number of instances in each cluster. The circles are coloured according to the acoustic class. Circles with a different coloured border indicate a cluster with a co-dominance of more than one acoustic class.

Figure 8.12b is an alternative view, where the radii of the circles are scaled to the 90th percentile of the distances between the medioid and the cluster elements, providing a means of displaying the relative volume occupied by each cluster. However, it should be noted that the clusters are not spherical, so the measure is at best an indication of cluster volume.

The Sammon map generally agrees with the acoustic class labels by grouping each acoustic class into its own space within the Sammon map. The quiet clusters (grey) are on the extreme right. They contain four large, but compact clusters (13, 31, 35, and 5 – see Appendix D for cluster sizes) as is evident by the comparison of Figures 8.12a and b. The orthopteran clusters (yellow) are grouped in the top right corner. The moderate to heavy rain clusters (10, 18, 59, and 60) in dark blue are positioned in the bottom left corner, diagonally opposite the quiet and orthopteran clusters. The wind and cicada clusters are closely positioned in the top left-hand corner.

The positions of the clusters are distributed along the x-axis according to amplitude. The louder clusters are on the left and the quieter clusters on the right. The largest bird cluster (Cluster 11) in terms of instances is centrally located. However, the morning chorus clusters and loud bird clusters (37, 43, and 58) are located towards the rain clusters in the lower left-hand corner. Varying acoustic bandwidth may distribute the clusters from the bottom-left to the top-right corner, rain sounds are broadband, and orthopteran calls are narrow band. The distribution along the ascending diagonal of the Sammon map shifts from highly percussive sounds such as rain through the short sharp calls of birds to the more continuous sounds of cicadas, orthopterans, and aircraft. Figure 8.13 summarises the general conclusions that can be drawn from the characteristics of the sounds located in each quadrant of the Sammon map.



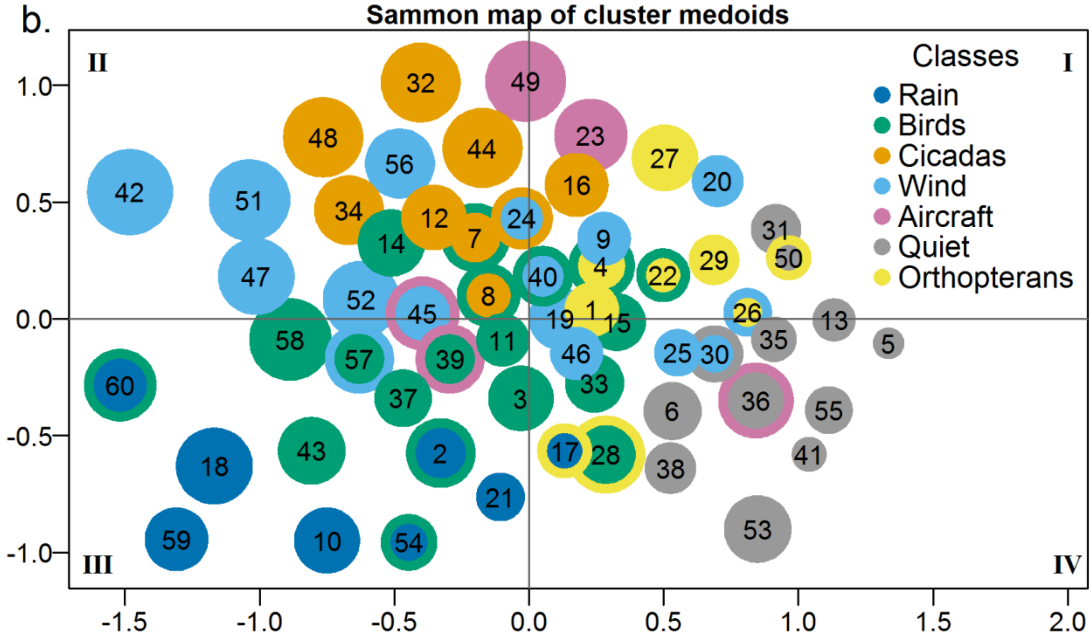


Figure 8.12 Sammon map of the medoids of the 60 clusters. a. The top image shows the circle radii in proportion to the number of cluster instances. b. The bottom image shows the circle radii in proportion to the ninetieth percentile of the distances between the medoid and the cluster instances. Drawn using the R package plotrix (Lemon, 2006). Image source: Phillips et al. (2018) doi:https://doi.org/10.1371/journal.pone.0193345.g006

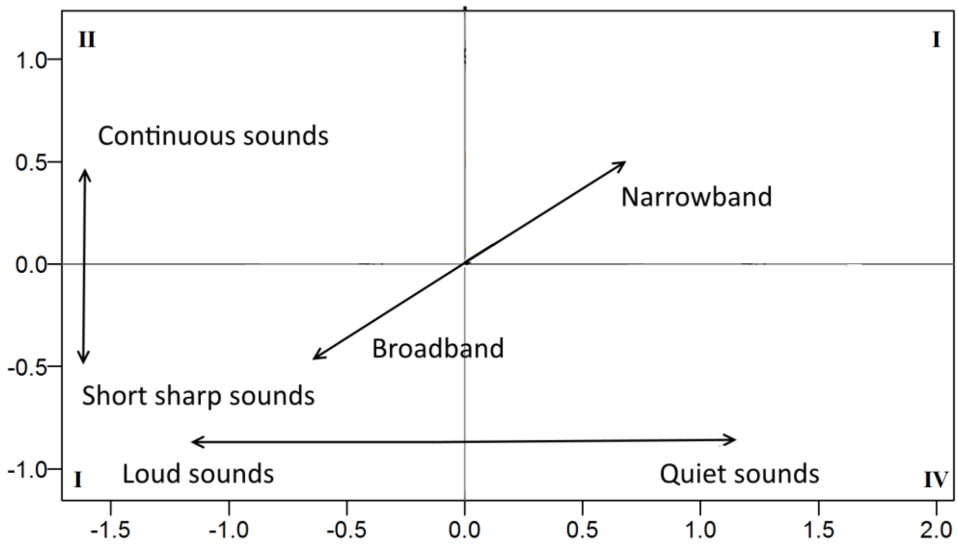


Figure 8.13 The Sammon map grid showing the general trends in the acoustic characteristics across the map. Notice there are general trends in the distribution of clusters in the up, down and diagonal directions according to different acoustic characteristics of the sounds in the clusters.

8.3.5 Examining the Radar Plots of Cluster Medoids

Radar plots (Figure 8.14 and 8.15) were used as the final method to verify the cluster identity. The radar plots map out normalised acoustic indices values of a random sample of 600 minutes from each cluster. The medoid as indicated by a black star plot, is the object that is most centrally located within the cluster.

Figure 8.14 contains radar plots from three acoustic classes, birds (cluster 37 and 3), orthopterans (clusters 29 and 1), and cicadas (clusters 48 and 44). Biophonic sound sources tend to have smaller normalised acoustic indices than geophonic sound sources such as wind and rain.

The bird clusters (Figure 8.14a and b – clusters 37 and 3) have peaks in MFC and ACI. The ‘morning chorus’ cluster (Figure 8.14a) has a higher BGN than the ‘daytime’ bird cluster (Figure 8.14b). BGN is known to increase during the morning chorus (Dabelsteen & Mathevon, 2002). SNR is higher in the daytime bird cluster when there are less overlapping birdcalls. There is low HFC because birdcalls rarely extend into the higher frequency range (greater than 8 kHz), although there are some exceptions.

The distinguishing features of the orthopteran clusters (Figure 8.14c and d) appear to be a small peak in EAS and very low CLC and ACI values. EAS peaks when the acoustic energy is concentrated in a narrow frequency band, which is the case when species of

Orthopterans for example crickets are calling. The low ACI values is in agreeance with the research of Fuller et al. (2015).

The cicada clusters (Figure 8.14e and f) are distinguished by very low ACI values and high ACT values. The low ACI is caused by the tendency of cicada calls to maintain a constant amplitude. The cicada calls in this study tended to be continuous which increases ACT, this acoustic index measures the number of frames above 3 dB. However, these observations are not consistent across all cicada species, some have ‘ticking’ calls (Ewart, 2005). Farina et al. (2011, see Figure 8 in their paper) and Ross et al. (2018) each found ACI was sensitive to cicada calls.

The rain clusters (Figure 8.15a and b) share similar peaks with the bird clusters with peaks in the ACI, EVN and CLC indices, however the values are much higher compared to the bird clusters. This explains why the rain and bird clusters share the same quadrant on the Sammon map (Figure 8.12). The parabolic curve formed between the BGN and SNR indicates the reciprocal nature of these indices, when BGN is high; SNR is low and vice versa.

The wind clusters (Figure 8.15c and d) are the most diverse group of clusters. As discussed previously, wind can occur in many different ways, different strengths, speeds, directions, the heights above the ground, in the canopy layer for example or at different distances from the recorder, all of which generate different acoustic qualities. Zhang, Towsey, Xie, Zhang and Roe (2016) found wind to be the most difficult acoustic class to classify with multi-label classifiers. Qi et al. (2007, p.204) recognises wind as being diffuse making it difficult to isolate and Mullet, Gage, Morton and Huettmann (2016) described a large proportion of geophony consists of sounds from distant sources that were “nearly inaudible”.

Strong wind, cluster 42 (Figure 8.15c) has high values of LFC, MFC and HFC indicating broadband sound, it spans to the full frequency range (0-11 kHz) of the recording. The very strong wind, cluster 47 (Figure 8.15d) has high values of BGN and CLC but reasonably low values of LFC, MFC and HFC. A review of cluster 42 and 47 indicates the sound of wind in cluster 42 is immediate to the recorder whereas the wind sounds in cluster 47 are further away in the tree canopy. Both clusters are similar in that they contain wind that varies in intensity across the one-minute samples.

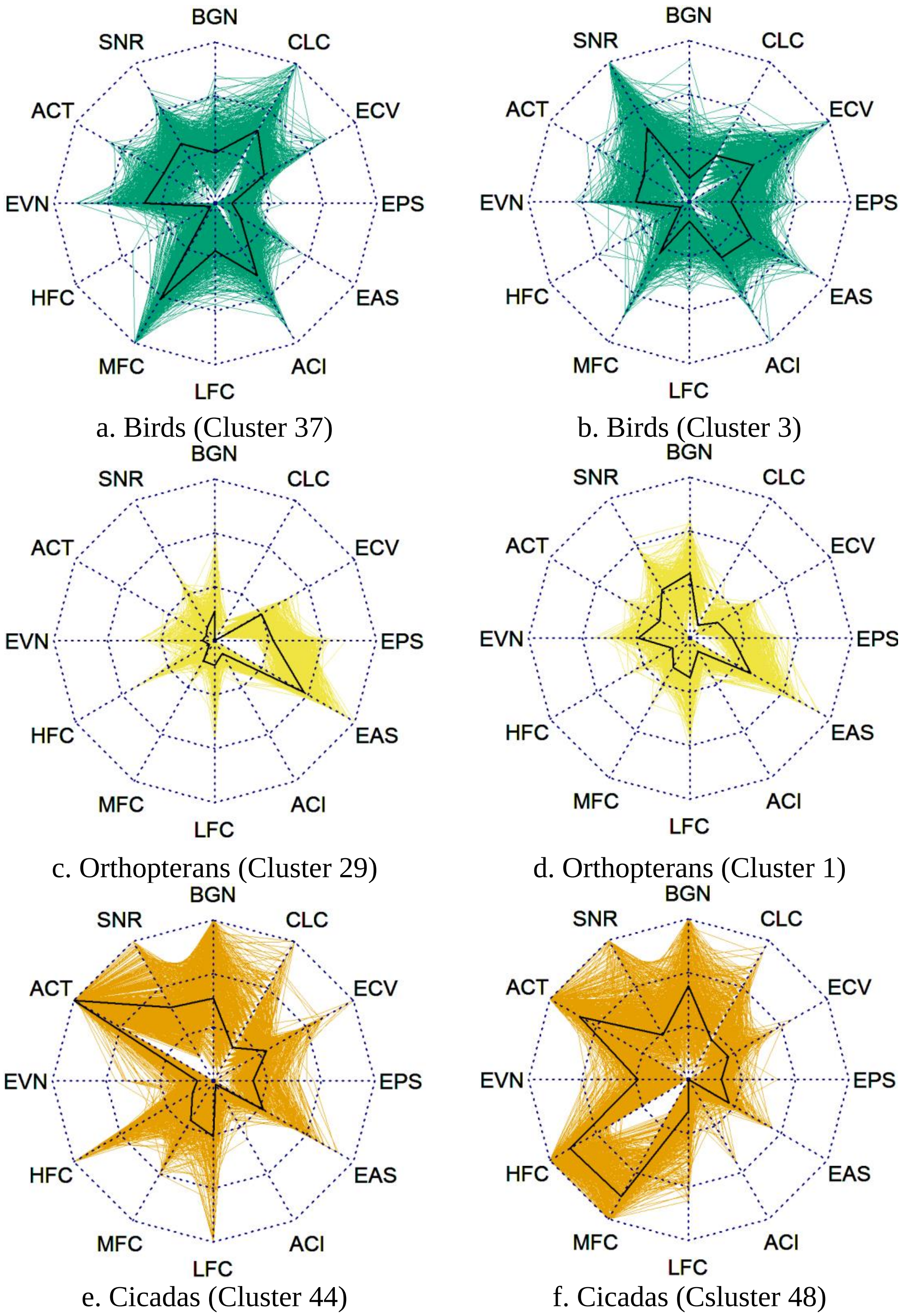


Figure 8.14 Radar plots of six clusters, two bird clusters (a and b), two orthopteran (c and d), and two cicada clusters (e and f). The solid black line maps the cluster medoid and the coloured lines are the mappings of 600 randomly sampled instances from each cluster. Produced using the R package ‘fmsb’ (Nakazawa, 2015).

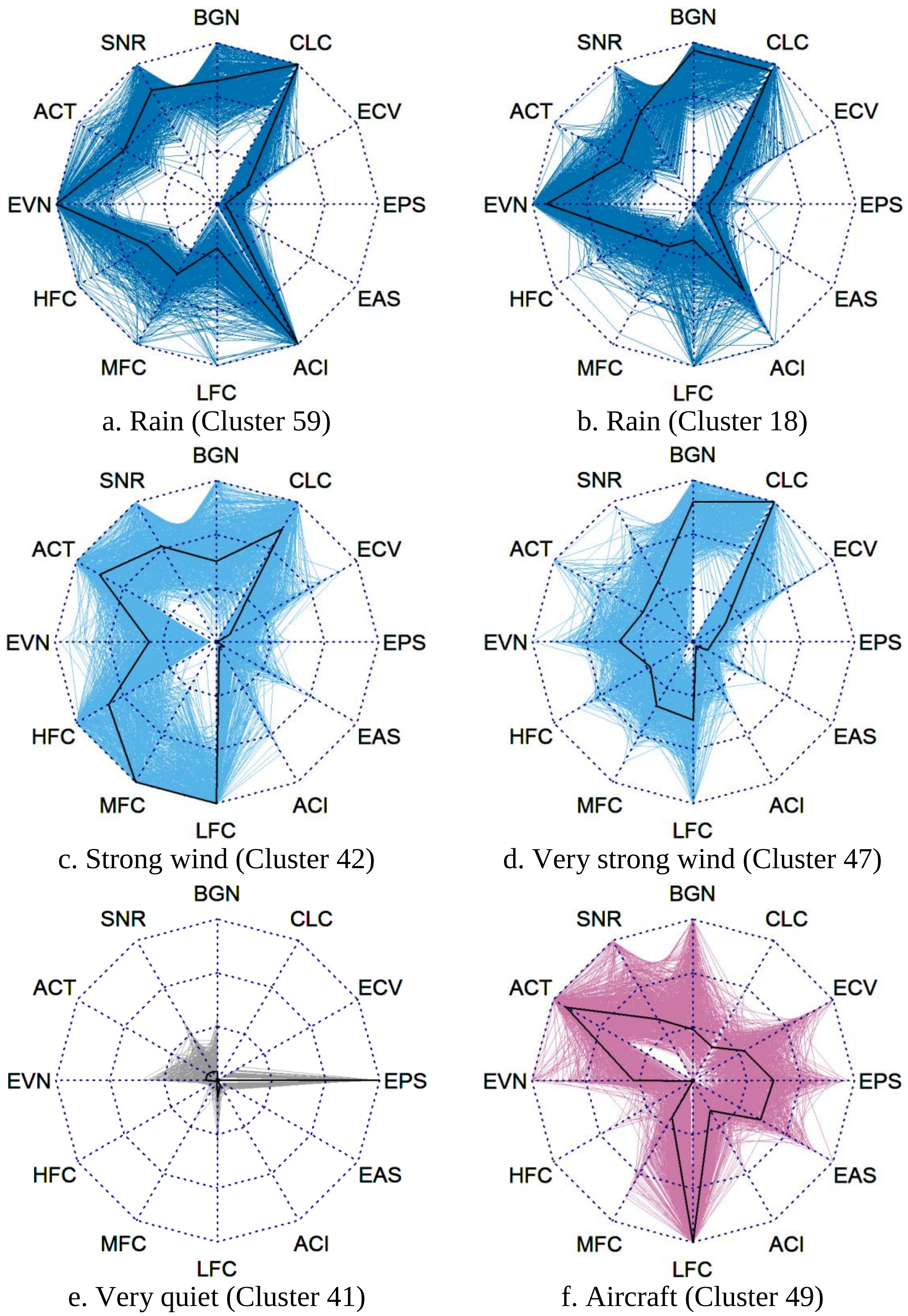


Figure 8.15 Radar plots of six clusters, two rain (a and b), two wind (c and d), one quiet cluster (e) and one aircraft cluster (f). The solid black line is the cluster medoid and the coloured lines are the mappings of 600 randomly sampled instances from each cluster. These are produced using the radarchart function in the R package 'fmsb' (Nakazawa, 2015).

The very quiet cluster, Cluster 41 (Figure 8.15e) has consistently low values of all acoustic indices except EPS, which is very high. The EVN index is detecting some sound events, which according to the sample listened to in this cluster were mostly very distant sounds.

The aircraft cluster, Cluster 49 (Figure 8.15f) is distinct because of the combination of the high LFC and low ACI as well as the high ACT values. ACT is high because aircraft are continuous, thus maintaining the decibel value above 3 dB. ACI is low because aircraft sounds are monotonous with little variation in amplitude (Farina, Pieretti, Salutari, Tognari & Lombardi, 2016; Pieretti et al., 2011). This very distinct combination of features is indicative of aircraft and could be diagnostic in determining this class of soundscapes.

A number of generalisations can be made about the acoustic classes in relation to the acoustic indices (see Figure 8.16). EPS is very low for the louder clusters including the morning chorus cluster, as well as the cicada, rain, and wind clusters. EPS is high for the quiet cluster and the orthopteran clusters. ACI and CLC are high for the bird and rain clusters and low for the orthopteran clusters. ACT is low for the more percussive sounds such as rain and high for the continuous sounds such as aircraft and insects.

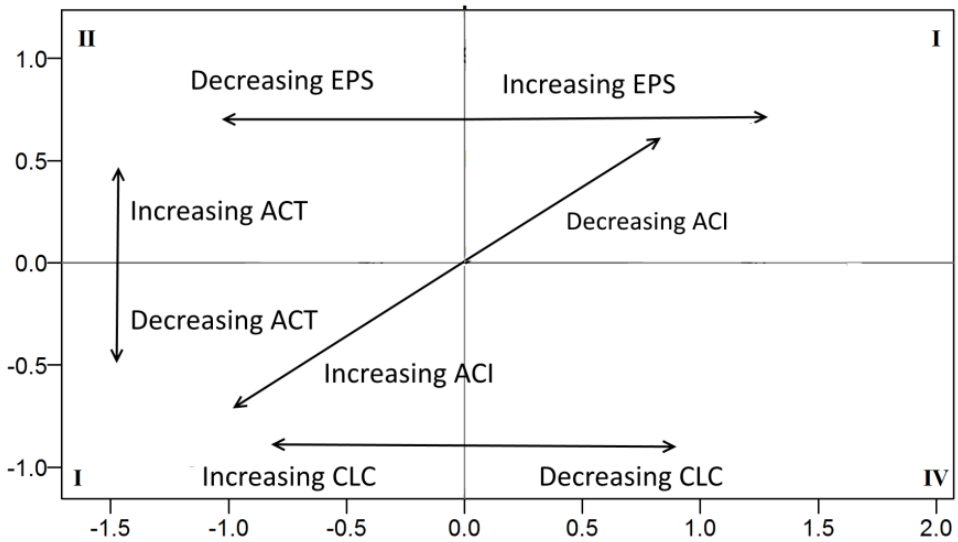


Figure 8.16 The Sammon map grid showing the general trends in the acoustic indices across the map. Notice there are general trends in the distribution of clusters in the up, down and diagonal directions according to some of the acoustic indices used in the clustering.

8.4 THE ACOUSTIC CLASS SEQUENCE

The application of the five methods (Section 8.3) allows a description to be given to each of the sixty clusters and the formation of the acoustic class sequence. The labels describe the acoustic class or the combination of acoustic classes that dominate the cluster. Table 8.1 provides a summary of 42 clusters containing only a single dominant sound source; these clusters occupied at least 73% of the total minutes. These clusters do not contain one sound source, but a single dominant sound source. Often other sound sources form the background sounds in the soundscape. It is important to note the following:

- The three largest acoustic classes are quiet, birds and wind.
- There are more wind clusters (10 wind clusters) than any other acoustic class (9 quiet clusters). This is not surprising because wind can vary in strength, direction, height where it is occurring and distance away from the recorder, all of which will cause variations in the sound of wind detected at the recorder.
- The total time of the rain acoustic class is not equal at each recording site. The Woondum National Park site has more than three times the number of minutes of rain.

Table 8.1 A statistical summary of the clusters containing one dominant sound source obtained by listening to a random sample of 20 one-minute audio segments from each cluster.

Acoustic class (label)	Description	Cluster IDs	% of total time assigned to acoustic class	
			Gympie National Park	Woondum National Park
Quiet	The absence of most sounds ranging from very quiet to quiet	5, 6, 13, 31, 35, 38, 41, 53, 55, 58	20.6%	26.2%
Birds	Birds calling	3, 11, 14, 15, 33, 37, 43	20.1%	14.4%
Wind	Sounds produced by air moving through and around objects	9, 19, 20, 25, 42, 46, 47, 51, 52, 56	15.8%	15.3%
Orthoptera	Sounds produced by insects mostly at night	1, 27, 29	9.1%	6.3%
Cicadas	Dawn-dusk and daytime cicada calls	12, 16, 32, 34, 44, 48	5.1%	5.5%
Rain	The sound of rain	10, 18, 21, 59	1.7%	5.6%
Aircraft	The sound of airplanes, motorbikes and other low frequency mechanical sounds such as helicopters	23, 49	0.9%	0.4%
CUMULATIVE TOTALS (42 CLUSTERS)			(73.3%)	(73.7%)

Table 8.2 summarises the remaining 18 of the 60 clusters. Part a, provides a summary of the clusters with two or three dominant sound sources. Part b contains clusters with inconsistent dominant sound sources. Eleven clusters, 19.3% of minutes, contained a mixture of two or three classes (Table 8.2a). Seven clusters, 7.2% of minutes were inconsistent, making their categorisation difficult (Table 8.2b). Inconsistent means these clusters contained minutes having a dominance of one sound source and other minutes with a dominance of another sound source. In these clusters, one dominant sound source is not consistent across the sampled minutes and does not meet the 85% criteria used when listening to the 20 minute sample; instead, there is an inconsistency of acoustic sources in these clusters

Table 8.2 a. A statistical summary of the clusters containing two or three dominant sound sources. b. The inconsistent dominant sound sources. Each obtained by listening to a 20-minute sample from each cluster.

Acoustic class (label)	Description	Cluster IDs	% of total time assigned to acoustic class	
			Gympie National Park	Woondum National Park
a. Two or three dominant sound sources				
Orthoptera/ Birds	Insects and birds calling	4, 22	7.8%	10.2%
Cicadas/ Birds/ Wind	Cicadas and birds calling along with wind	7, 8	5.1%	2.6%
Rain/Birds	Birds calling during rain	2, 54, 60	1.6%	3.9%
Birds/ Quiet	A few bird calls with a quiet background	30	2.0%	1.3%
Birds/ Aircraft	Birds calling and the sound of aircraft	39	2.1%	1.3%
Orthoptera/ Wind	Distant insects in quiet background or wind	26	0.3%	0.9%
Wind/ Aircraft/ Orthoptera	Moderate wind with aircraft and insects	45	0.5%	0.1%
CUMULATIVE TOTALS (11 CLUSTERS)			19.4%	19.3%
b. Inconsistent sound sources				
Wind/ Birds	Inconsistent: Wind and Birds or Insects and wind	40	1.5%	1.9%
Light rain/ Orthoptera	Inconsistent: Light rain or Insects	17	0.9%	2.3%
Birds/ Aircraft/ Orthoptera	Inconsistent: Birds, Insects or Aircraft	28	2.0%	0.5%
Quiet/ Aircraft	Inconsistent: Quiet and distant aircraft	36	1.5%	0.7%
Wind/ Cicadas	Inconsistent: Wind and/ or cicadas	24	1.1%	0.7%
Quiet/ Birds Orthoptera	Inconsistent: Quiet and insects and/or birds	50	0.3%	0.6%
Birds/ Wind	Inconsistent: Birds or wind	57	0.1%	0.3%
CUMULATIVE TOTALS (7 CLUSTERS)			7.4%	7.0%

An acoustic class sequence is formed by allocating a single acoustic class to each cluster. Most of the clusters had a single dominant sound source. The clusters with two or more dominant sound sources (Table 8.2a) were allocated to the acoustic class that was listed first in the acoustic class (label) column in the table; this was the acoustic class that was most dominant in the sample. The clusters with inconsistent sound sources (Table 8.2b) were given an acoustic class label that reflects the most common sound source in the sample. An acoustic class sequence is formed from the labels given to each cluster. This acoustic class sequence will be used for visualisation in Chapter 9.

8.5 SUMMARY

This chapter described the clustering of the thirteen-month datasets and the interpretation of the clusters obtained. The results indicate that hybrid clustering produced clusters that were acoustically and ecologically meaningful. That is, it was possible to interpret most of the clusters by listening, and these could be related to the source of the sound. The temporal distribution of these clusters displayed patterns that matched expected daily and seasonal patterns indicating that these were ecological in origin.

One-minute audio segments are commonly used in ecoacoustic analysis (Farina & Salutari, 2016). Although it is uncertain, the use of shorter segments could improve the separation of the sounds for example the thunder from the airplane acoustic class.

The sounds in a natural environment originate from different sources, birds, insects, wind, rain, and mechanical sounds. The sounds from birds are produced differently to the sounds of other animals. The physical differences in the sound producing structures of different animals produced differences in the sound itself, which enabled the acoustic indices, through clustering to distinguish these sound sources.

The five methods used to evaluate and verify the clustering result, confirmed that most of the clusters were reasonably discrete. Some clusters contained sounds from a mixture of dominant sound sources as is to be expected. A small percentage of clusters (7.2%) were not easily classified. However, these were given a classification according to the most common sound source it contained. Certain infrequent sounds such as thunder do not form their own cluster instead are clustered with another sound source, aircraft. They were grouped with the acoustic class which best matched the acoustic features that were measured. There was no acoustic class for frogs because their calls were rare in the recordings due to the distance the recording site was from a permanent water source.

The biophonic and quiet acoustic classes had meaningful temporal distributions. The temporal distribution of the bird morning chorus clusters aligned closely with the period before sunrise and peaked during the breeding season. The cicada clusters were contained to the months in which the cicadas occur. The orthopterans increased during spring and dominate the summer months. The quiet clusters mostly occur during the cooler months. These examples provide the evidence that the cluster result had ecological significance.

Some indices are highly diagnostic of particular acoustic classes, for example, ACI is indicative of rain, and LFC of aircraft or wind. Acoustic classes lying within the same quadrant of the Sammon map (Figure 8.12) have similar radar plots. The further the cluster is from the centre of the Sammon map the higher or lower the acoustic indices values are. It was the *combination* of acoustic indices not single acoustic indices that were responsible for separating the different soundscapes into acoustic classes.

Chapter 9

Visualising the Acoustic Class Sequence

In the last chapter, each cluster was assigned to an acoustic class. The *acoustic class sequence* was generated consisting of one label for each recorded minute in the 13-month audio recordings. In this chapter, the acoustic class sequence is visualised. The first three-visualisation techniques described, each present a different summary of the acoustic state sequence. The visualisations will enable the interpretation of the ecological information contained within the very-long-duration audio recording. A visualisation technique is also developed to display the microphone malfunction.

9.1 OVERVIEW

This chapter is the second of two chapters that address objective 3, the development of visualisation techniques for the interpretation and navigation of long-duration audio recordings. Audio navigation is the process of determining the position of a sound event within an audio recording. The acoustic class sequence is visualised using three techniques, dot-matrix plots, polar histograms and cluster diel plots, each designed to reveal a different aspect of the data.

9.2 DOT-MATRIX PLOTS

Dot-matrix plots (Figures 9.1 and 9.2) in the way they have been used in this research is a form of temporal graph (Dale, 2017, p.164-168). They have been used previously to display the similarity between different amino acid sequences or the repetition of sequence elements across amino acid sequences (Gibbs & McIntyre, 1970). In this case the plots were used to compare sequences. Here dot-matrix plots are adapted to display the repetition of acoustic state sequences across a twenty-four hour period.

9.2.1 The Preparation of Dot-Matrix Plots

The sixty clusters were combined into one of the seven acoustic classes by combining clusters with the same acoustic class label. Each acoustic class was given a colour (Table 9.1).

Table 9.1 The colours used to display each acoustic class, the RGB and hexadecimal string colours are provided.

Acoustic Class	Colour name	RGB (Wong, 2011).	Hexadecimal string (HEX)
Rain	Dark blue	0, 114, 178	#0072B2
Wind	Light blue	86, 180, 233	#56B4E9
Birds	Green	0, 158, 115	#009E73
Orthopterans	Yellow	240, 228, 66	#F0E442
Cicadas	Orange	230, 159, 0	#E69F00
Aircraft	Purple	204, 121, 167	#CC79A7
Quiet	Grey	153, 153, 153	#999999

Dot matrix plots consist of a 1440 $\times$ 1440 matrix. The horizontal and vertical dimensions of the matrix represent the minutes within a 24-hour period. The sequence of acoustic states within a 24-hour period is plotted on the ascending diagonal using the colours from Table 9.1. The squares at the intersection of matching acoustic classes are filled with the colour matching the acoustic class.

9.2.2 The Interpretation of Dot-Matrix Plots

Corresponding dot-matrix plots are provided, six from each the Gympie National Park site (Figure 9.1) and the Woondum National Park site (Figure 9.2). Each image has a vertical grid indicating each two-hour period. There is an overlay of thicker black dotted lines marking the time of civil dawn, sunrise, sunset and civil dusk.

A typical soundscape during winter (Figures 9.1a and 9.2a) consists of two acoustic states, quiet (grey) at night and birds (green) during the day. This typical pattern changes after rain (Figures 9.1b and 9.2b) when orthopterans are calling at night. Birds continue to call during the day and between the rain periods.

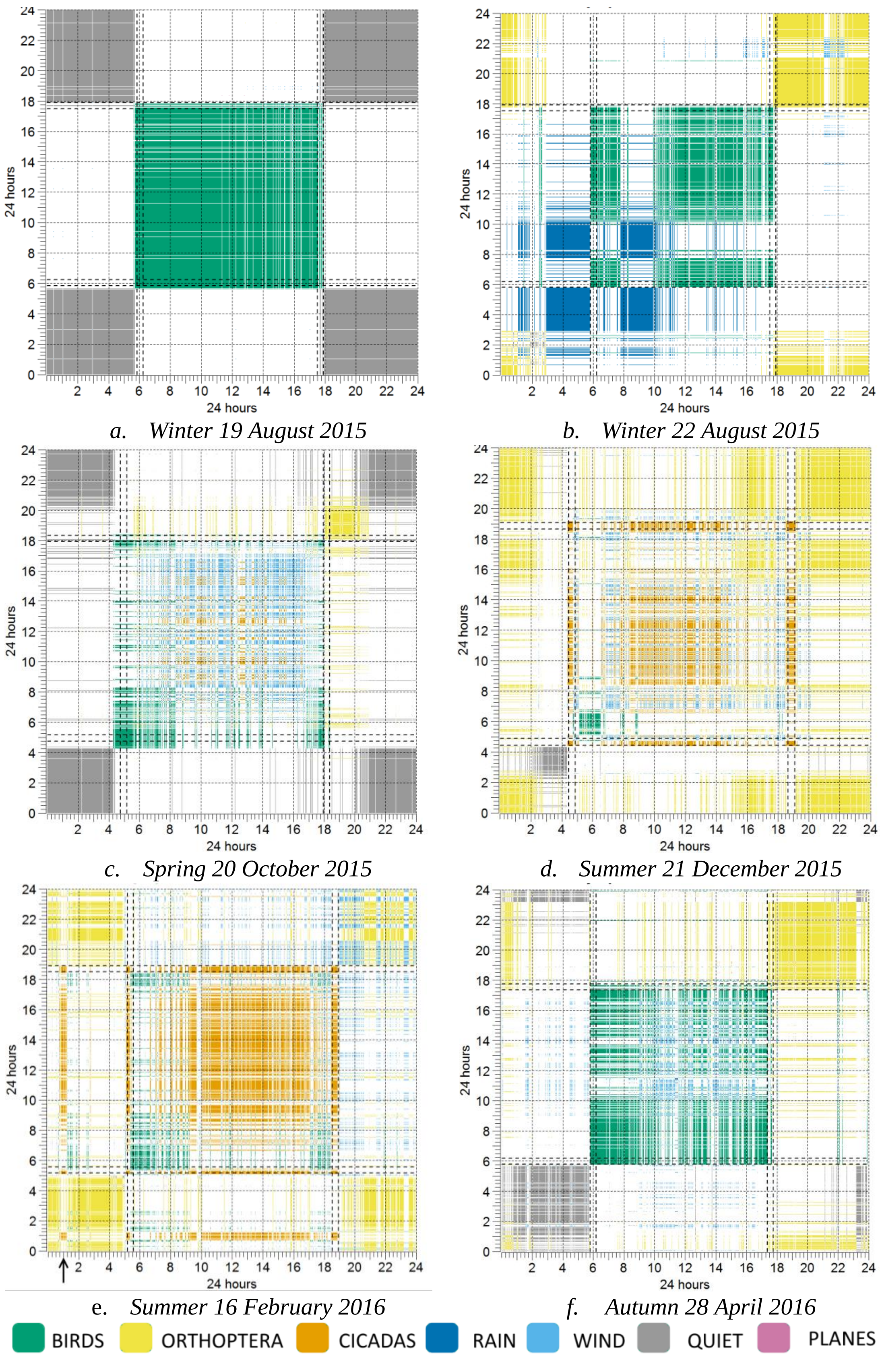


Figure 9.1 Dot-matrix plots of six days revealing seasonal changes in the acoustic soundscape at Gympie National Park. The date and season are provided below the figure. The civil dawn, sunrise, sunset and civil dusk is shown with darker lines.

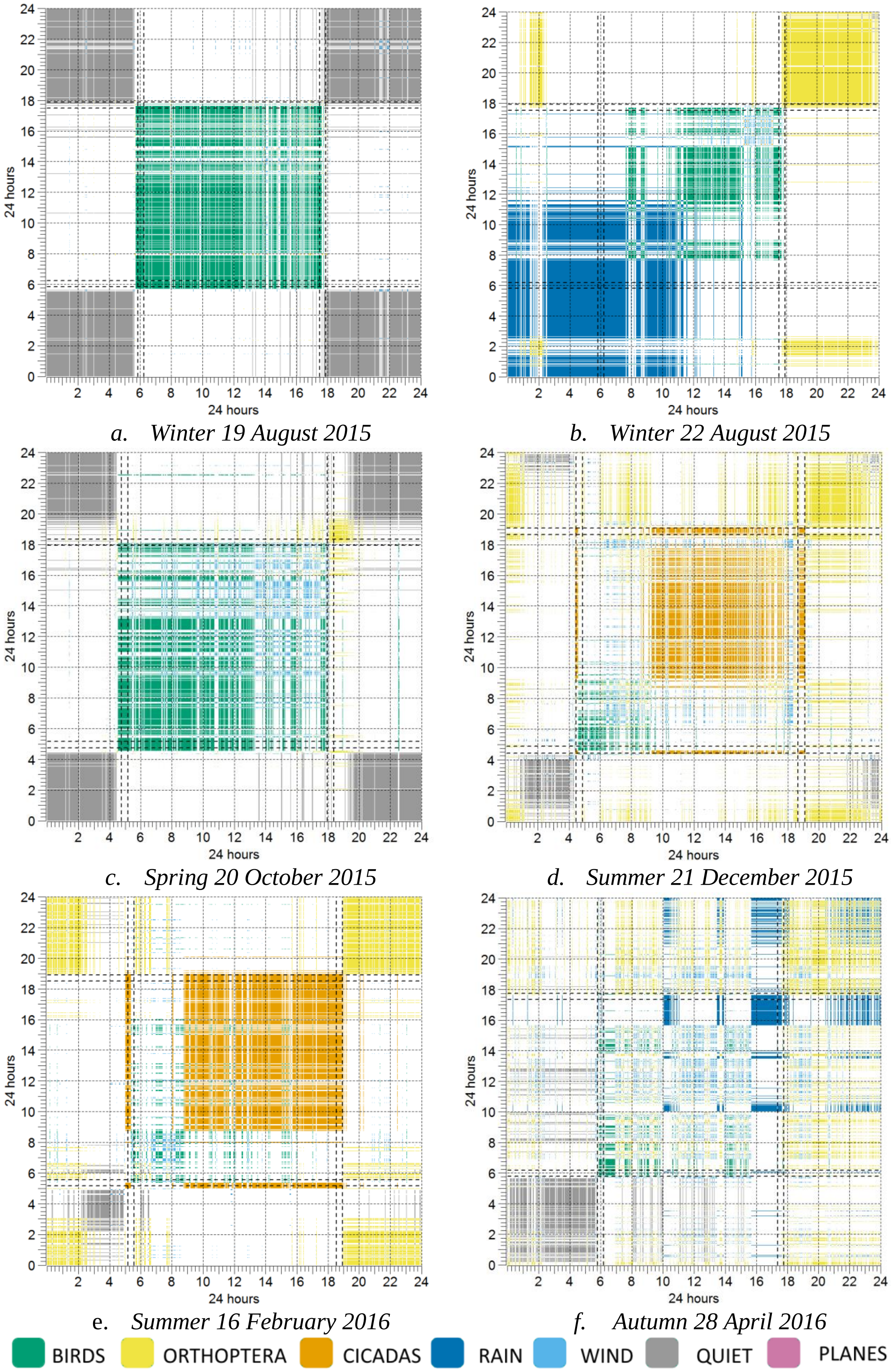


Figure 9.2 Dot-matrix plots of six days revealing seasonal changes in the acoustic soundscape at Woondum National Park. The civil dawn, sunrise, sunset and civil dusk is shown with darker lines.

During spring (Figures 9.1c and 9.2c), the birds start calling around 4:10 am, one hour before sunrise (5:10 am). The nights are mostly quiet with orthopteran calls occupying the early evening. The Bark Squeaker (*Pauropsalta corticinus*) cicada is calling intermittently throughout the day at Gympie National Park (Figure 9.1c) from 6:36 am to 4:35 pm.

At Woondum National Park (Figure 9.2c), the Bark Squeaker cicada was calling intermittently during the morning but was distant from the recorder forming background sound rather than dominant foreground sound. Birds were calling much closer to the recorder. There was recurrent wind throughout the afternoon.

Cicadas during the day and orthopterans at night, dominate in summer (Figures 9.1d and 9.2d). The summer season has very little "quiet" and the cicada chorus at dawn interrupts the bird morning chorus, this is repeated at dusk. For at least one species, the Australian Bladder Cicada (*Cystosoma saundersii*), the occurrence of calling at dusk is believed to be related to the avoidance of predators (Doolan & Mac Nally, 1981).

Birds do not dominate the soundscape during summer due to the presence of cicada calls during the day. Summer is the only season when the birds do not dominate the daytime soundscape. The second pair of summer images (Figures 9.1e and 9.2e) confirms the soundscape pattern in Figures 9.1d and 9.2d. However, there appears to be something unusual occurring between 12:45 am and 1:15 am in the Gympie National Park image (Figure 9.1e – marked with an arrow). The orange in Figure 9.1e indicates that cicadas are calling at night. Upon listening to the recording, this was not found to be the case. This period instead corresponds to the echolocation call of the White-striped Free-tailed Bat (*Austronomus australis*). This bat calls in the high frequency range above 7 kHz. This irregularity in the acoustic class is understandable because the bat calls are in the high frequency range similar to that of one of the cicada species common to the site. The bats call is in the human audible range, which is unusual as most echolocation calls are ultrasonic (frequencies above 20 kHz). The ribbon plots were useful in identifying the presence of this bat species (Towsey et al., 2018b).

By autumn (28 April 2016 - Figure 9.1f and 9.2f) the cicadas have disappeared. The birdcalls return to the dominant place in the daytime soundscape. The nights are quieter with orthopteran calling less during the night and the hours before sunrise have mostly returned to quiet. The descriptions made for the interpretation of the dot-matrix plots were authenticated by referring to the original audio recordings and/or the LDFC spectrograms.

The two recording sites are twenty-five kilometres apart; due to this, the sites have similar soundscapes. Regional weather patterns such as rain events are observed, however local weather patterns are also reflected. The Woondum National Park site has higher rainfall, for example, and differences in local wind, bird and insect calling is also reflected in these images.

9.3 POLAR HISTOGRAMS

Polar histograms (Figure 9.3) provide an overview of the thirteen-month audio recordings. These plots show the proportion of each acoustic class occurring each day, displaying the changes in each acoustic class over time and seasons.

9.3.1 The Preparation of Polar Histograms

Polar histograms are prepared by determining the number of minutes in each of the seven acoustic states each day. An adaptation of the 'polarhistogram' R code written by Ladroue (2012) (after Kettunen et al., 2012) was used to produce these plots. The adapted code is available (see Appendix A).

9.3.2 The Interpretation of Polar Histograms

The advantage of polar histograms is that they display the proportion of each acoustic class across months and seasons, which allows a narrative to be told about the seasonal changes in the soundscape.

The Gympie National Park site (Figure 9.3a) has a peak in bird calling during autumn, winter, and spring. The bird calling drops in October 2015 when the daytime cicadas commence. The cicada calling remains reasonably constant throughout late spring and summer. The wind is greatest from late January to early April 2016. The amount of quiet is at a peak during winter and spring when there is very little orthoptera calling.

When the soundscapes from the two recording sites (Figure 9.3) are compared, there is less bird calling during winter and more during mid-spring (October 2015) at the Woondum National Park recording site before decreasing during November 2015. The cicadas do not play a significant role in the soundscape at the Woondum National Park site until late November 2015 in contrast to the earlier calling at Gympie National Park. Different species of cicada are known to be associated with different tree species and different species call during different months (Kwok & Emery, 2016). The identified cicada species are listed in Appendix B and this indicates difference in species at each site.

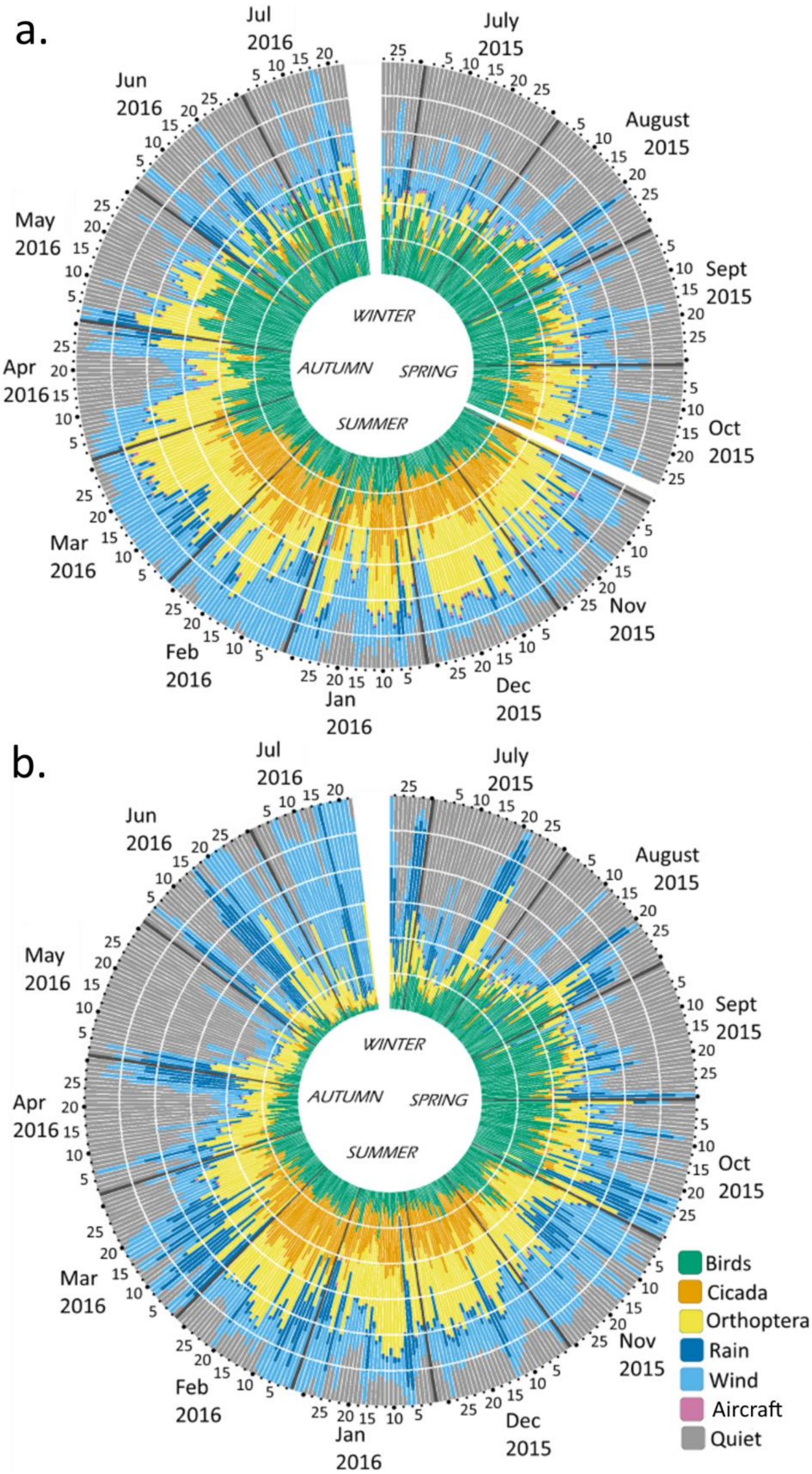


Figure 9.3a. The polar histogram of the Gympie National Park recording. Birds dominate the soundscape during the winter months, cicadas, & orthoptera during summer. The circular grid lines (white) mark each four-hour period & the radial grid lines (black) demarcate the months. Three days of recording October 28 to October 30 2015 were not clustered due to microphone problems (see Section 4.3). b. The polar histogram of the Woondum National Park recording. The soundscape is dominated by birds during late winter & early spring and cicadas & orthoptera dominate summer. This site has significantly more rain. Following rain there appears to be an associated increase in orthopteran calling.

9.4 CLUSTER DIEL PLOTS

9.4.1 The Preparation of Cluster Diel Plots

Cluster diel plots (Figure 9.4) are prepared by plotting a series of rows containing a sequence of 1440 squares representing the minutes in each day. The number of rows equals the number of recorded days. Each colour represents a different acoustic class; the colours remain the same as those defined in Table 9.1. The dotted curved lines represent the time of the civil-sunrise, sunrise, sunset, and civil-sunset. Days are consecutively arranged from the first day of recording at the top to the last day at the bottom.

9.4.2 The Interpretation of Cluster Diel Plots

Cluster diel plots are maps of the soundscape; they display the temporality of the acoustic classes. These maps provide the "what", "when" and "how long" of the acoustic classes. The night soundscape is dominated by quiet and orthoptera and the day by birds, wind and cicadas. The daily commencement of birds occurs at or before civil-dawn.

The most dramatic changes in the soundscape occur during dawn and dusk, the time of transitions between day and night and vice versa. Birds concentrate their calling during the morning, commencing at or before civil dawn. Bird calling is less during the remainder of the day. Orthopterans most commonly commence calling at dusk although they also call during the day (Gasc et al., 2017).

Cicada species call during the day and at dawn and dusk. The cicadas calling during dawn at Gympie National Park (Figure 9.4a) call for a short period (usually between 7 and 20 minutes) commencing at or just before civil-dawn on most mornings from the 20th November 2015 to the 8 March 2016. At Woondum National Park (Figure 9.4b), the cicadas call for around 10 to 20 minutes on most mornings.

The cicadas calling at dusk at both recording sites generally call between sunset and civil-sunset. The dusk cicada chorus occurs over a longer period and can continue for up to one hour. The dawn cicada chorusing was sustained at the Woondum National Park site (Figure 9.4b) until the 5 April 2016 and the dusk chorusing until the 9 April 2016. April is when the night-time temperatures begin to be noticeably cooler (see Figure 3.2).

Orthopteran calling occurs most frequently after sunset during spring, summer, and autumn (Figure 9.4). The orthopteran calling becomes consistent after sunset at the Gympie National Park site on the 25 September 2015, when the orthopterans displace the 'quiet' acoustic class after sunset. At the Woondum National Park site, this occurs on the 28 September 2015. Temperature regulates the time of insect calling (Doolan & Mac Nally, 1981; Van Wyk & Ferguson, 1995). During winter and early spring, orthopteran calling occurs at night during the days after rain.

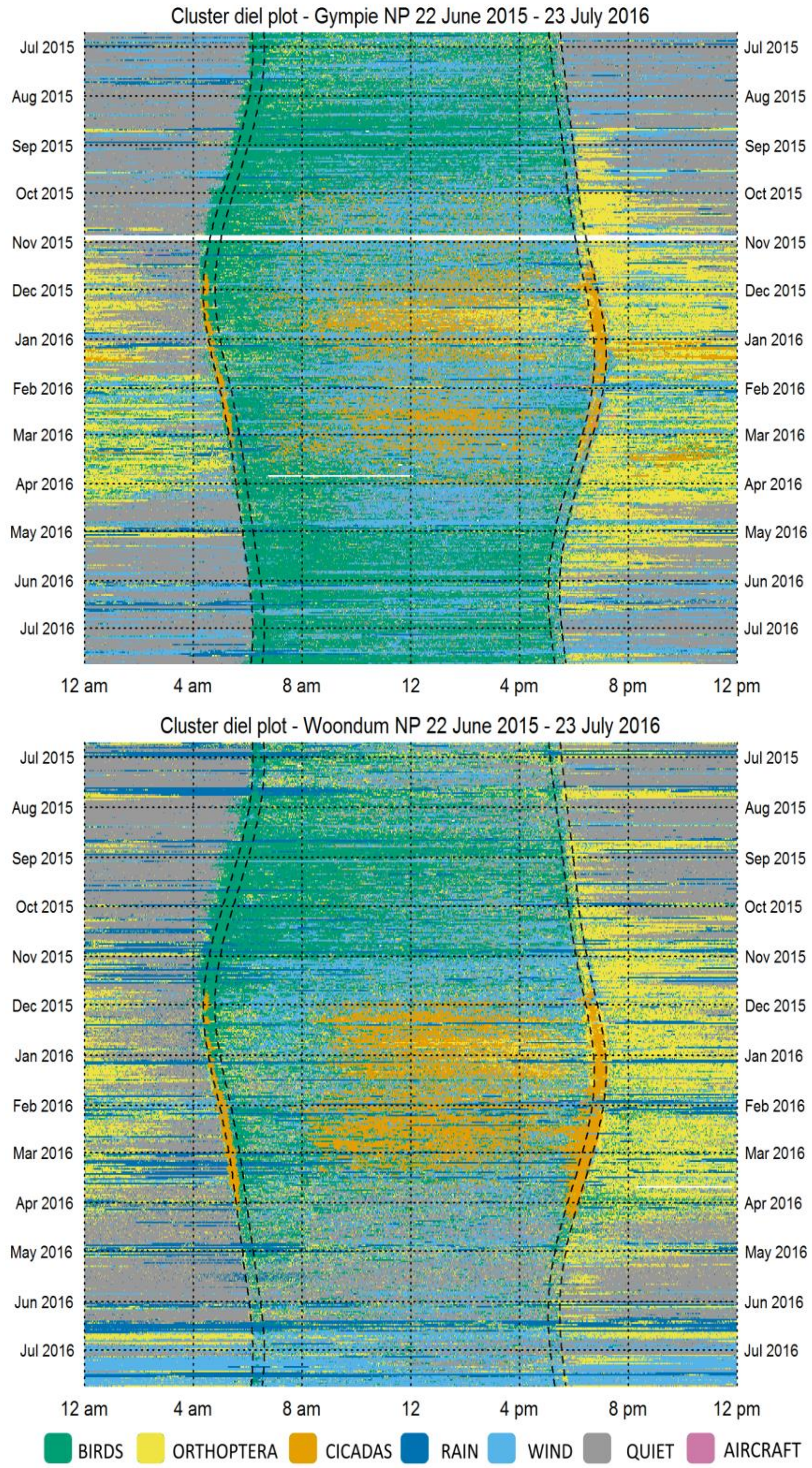


Figure 9.4a. The cluster diel plot of the Gympie National Park recording. b. The cluster diel plot of the Woondum National Park recording. Rain is more prevalent at the Woondum National Park site compared to the Gympie National Park site. The curved lines represent civil-sunrise, sunrise, sunset and civil sunset.

Each technique visualises the seven acoustic classes using seven colours. This one to one correspondence of colours to a specific data element (Aigner, Miksch, Schumann & Tominski, 2011, p.90) allows the ready interpretation of these images. Healey (1996) and Healey and Enns (2012) assert that seven is the maximum number of colours that humans can simultaneously perceive.

9.5 CHANNEL INTEGRITY PLOTS

Before leaving the visualisation of the clusters, a return to the microphone malfunction is made. The decision tree classifier in Chapter 5 enabled the classification of the microphone malfunction. This enables the visualisation of the channel integrity, the reliability of the data in both recording channels.

9.5.1 Preparation of Channel Integrity Plots

The decision tree classifier (Figure 5.3) indicates the decibel difference of 4.534 dB separates most of the instances labelled 'not' from those labelled 'left affected'. The channel integrity (Figure 9.5) was visualised using a two-tone colouring technique (Saito et al., 2005). This technique uses a series of vertical lines consisting of two colours, which are plotted to build up an image representing changes in the decibel difference. For each day, 1440 vertical lines are plotted; the two colours consist of the colour representing the scale and the colour representing the scale interval below.

For the purpose of this plot, any decibel difference value above 7.5 dB was reduced to 7.5 dB. The scale intervals and colours used were 0 to 1.49 (light blue), 1.5 to 2.99 (green), 3.0 to 4.49 (yellow), 4.5 to 5.99 (orange) and above 6.0 (red). Dark blue was used as the background colour in the first scale interval.

The microphone malfunction occurred after rain. Figure 9.6 shows the periods of moderate to heavy rainfall at Gympie National Park as determined by the moderate and heavy rain clusters in the cluster list. There is a correlation between the periods of microphone failure (Figure 9.5) and the periods of rain (Figure 9.6). The lag in days between the number of minutes of moderate and heavy rain (clusters 2, 10, 17, 18, 21, 54, and 59) in a 24-hour period and the number of minutes with a decibel difference greater than 4.53 dB is 0 to 2 days (Figure 9.7). The days from the 6 July 2015 to 6 January 2016, excluding the 28 to 30 October 2015 were used, a total of 182 days. The three days from the 28 to 30 October 2015 were removed before clustering (Section 4.3). Therefore, the rain periods during this period cannot be provided. The lag indicates that microphone malfunction usually lasted for at least two days in the Gympie National Park recorder following rain.

The left microphone was replaced on the 7 January 2016. When the replacement microphone was found not to be functioning, it was replaced on the 24 January 2016. The seventeen days of microphone failure is clearly indicated (Figure 9.5).

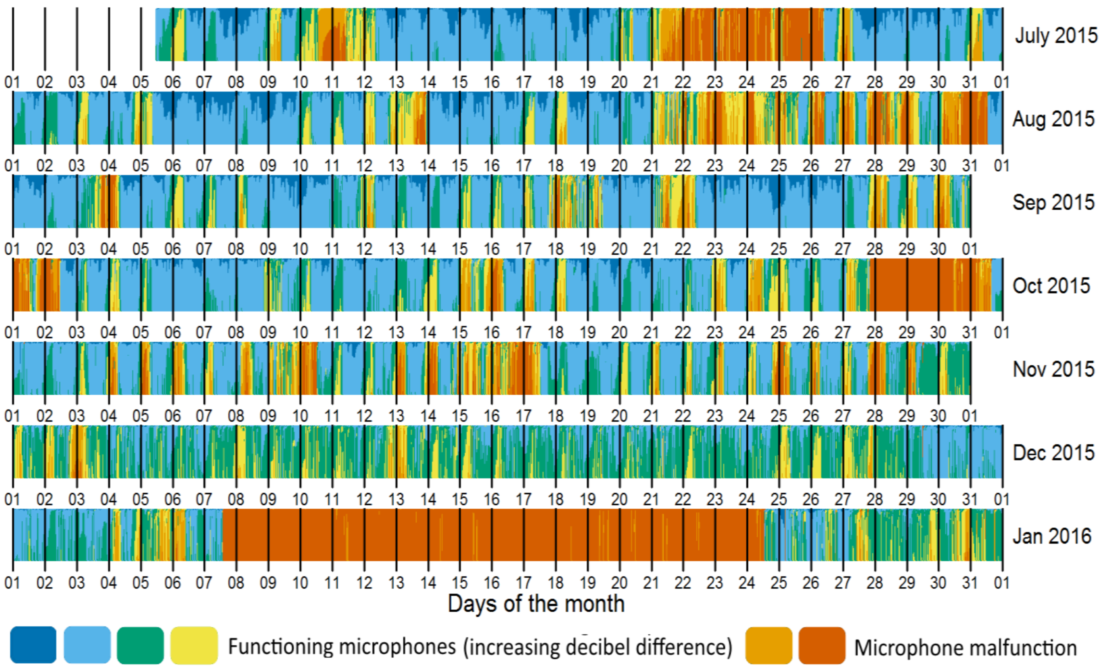


Figure 9.5 Channel integrity plot shows the periods of microphone malfunction in the Gympie National Park recording from the 5 July 2015 to the 31 January 2016 using the colouring technique by Saito et al. (2005). The six-colour scale shows the increasing decibel difference, orange and red represent values greater than 4.5 dB, therefore these colours indicate microphone malfunction.

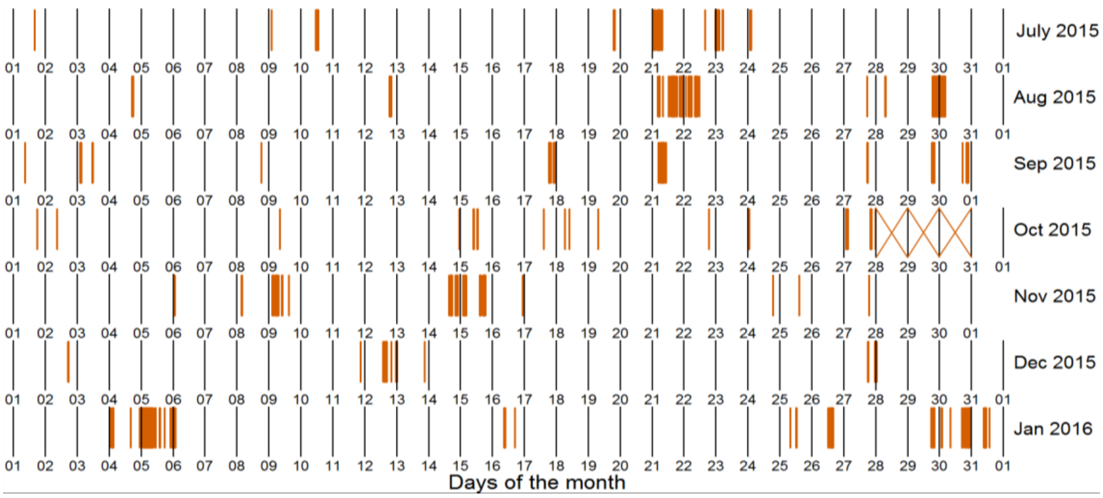


Figure 9.6 The occurrence of moderate and heavy rain for the months of July 2015 to January 2016, these times were determined from the cluster result. Note the 28 to the 30 October are not included because on these days both microphones failed and were removed from the clustering.

The channel integrity plot uses a range of six colours chosen to make values easy to interpret. The colours used for the lower decibel difference are cooler colours, light, and dark blue. The mid-range values are represented by green and yellow, these colours draw more of the viewers' attention. The warmest colours represent the values above 4.5 dB; these colours command the most attention. The warm colours alert to the periods of microphone malfunction.

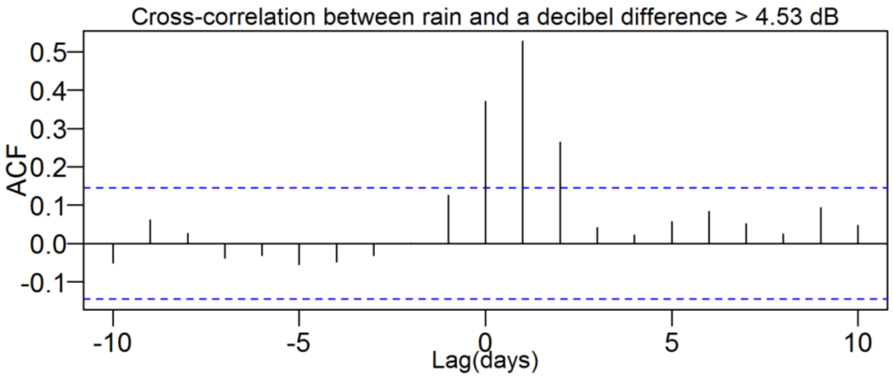


Figure 9.7 Cross-correlation between the number of minutes of moderate or heavy rain in 24 hours and the number of minutes where the decibel difference has greater than 4.53 dB. The dotted blue horizontal lines mark the 95% confidence interval (±1.96/√d where d is 182 days).

9.5.2 Interpretation of the Channel Integrity Plot

Before the microphone was replaced on the 7 January 2016, the left microphone was malfunctioning after moderate to heavy rain. The time taken for the microphone to recover was shorter during late spring and summer (November 2015 to January 2016), however additional rain will extend the recovery time.

There is a shift in the appearance of Figure 9.5 in late November 2015. During July to the 27 November 2015, the image is mostly blue indicating a decibel difference between the channels of below 1.5 dB. However, from the 28 November 2015 onwards the image appears mostly green and yellow. The green and yellow indicates a decibel difference of between 1.5 and 4.5 dB. It is thought the commencement of the daytime cicadas around the end of November 2015, may increase the decibel difference between the channels due to the directional difference in the amplitude of the cicada calls.

9.6 SUMMARY

The first three visualisation techniques described in this chapter, dot-matrix plots, polar-histograms and cluster diel plots were designed to provide alternative ways of visualising the acoustic class sequence. Each technique is different in purpose and each facilitates the interaction with the original audio recording by indexing the time and date reference. The acoustic class sequence in this case obtained from clustering represents the acoustic class of each one-minute audio segment. The dot-matrix plot provides a 24-hour model of the soundscape. These models when compared can determine what the typical soundscape is for a particular season and site. These plots could be used to demonstrate differences in vocal species across elevational gradients (Campos-Cerqueira & Aide, 2017).

Dot-matrix plots allow the examination of the structure of the soundscape across the day, in particular the persistence and repetition of each acoustic class. The use of colours improves the interpretation of acoustic class patterns. These plots can be used to examine the timing of the morning chorus in relation to civil-dawn and sunrise.

Polar histograms display the acoustic class information to allow associations to be made between an acoustic class and season or between acoustic states, for example, rain and insects. These plots could be used to compare the stability of ecosystems or to investigate the effect of perturbations such as cyclones and fires.

Cluster diel plots are representative of the timing of sound in the environment. First time observers of these images quickly start to interpret the image through the knowledge they already have about environmental soundscapes. These plots also allow the further construction of knowledge increasing the understanding of the soundscape at a particular location. They facilitate the interpretation of a very-long-duration audio recording, which would otherwise remain impenetrable. These plots have the potential to significantly extend our understanding of the association between the different components of soundscapes and the environment and could be used to monitor climate change and habitat regeneration.

The channel integrity plot (Figure 9.5) enables the interpretation of microphone malfunction in very-long-duration audio recordings.

Chapter 10

Acoustic State Cycles: Case Studies

The last chapter provided a broad-scale interpretation of the audio recording through the visualisation of the acoustic state sequence. Recall that each cluster is treated as a discrete acoustic state. This chapter extends the interpretation of the 13-month audio recording through the detailed examination of daily, monthly, and seasonal cycles within the acoustic state sequence. Six case studies were conducted and the findings establish that the contents of the 60 clusters can be further understood through the study of the acoustic class sequence.

10.1 OVERVIEW

The six case studies investigate different acoustic phenomena associated with different ecological processes. The patterns investigated include the daily dawn and dusk calling cycles of birds and cicadas and acoustic community responses to abiotic factors, such as rain and temperature.

10.2 CASE STUDY 1: THE STRUCTURE OF THE CICADA DAWN AND DUSK CHORUS

This study was conducted using the acoustic class sequence from Section 8.4 and the LDFC spectrograms. Patterns of cicada choruses are noted in the LDFC spectrograms during dawn and dusk (Figure 10.1). The timing of these patterns in relation to civil dawn and civil dusk are then related to specific clusters within the acoustic class sequence.

The dawn and dusk cicada choruses are a dominant part of the summer soundscape. The chorus of the Razor Grinder Cicada (*Henicopsaltria eydouxii)* stands out clearly in LDFC spectrograms as a bright red patch in the frequency range of 2-6 kHz (Figure 10.1) also see Figure 6.3. A closer examination reveals the first and last minutes of the cicada chorus appear different to the main part of the chorus, these minutes appear, blue-green, in these images instead of bright red.

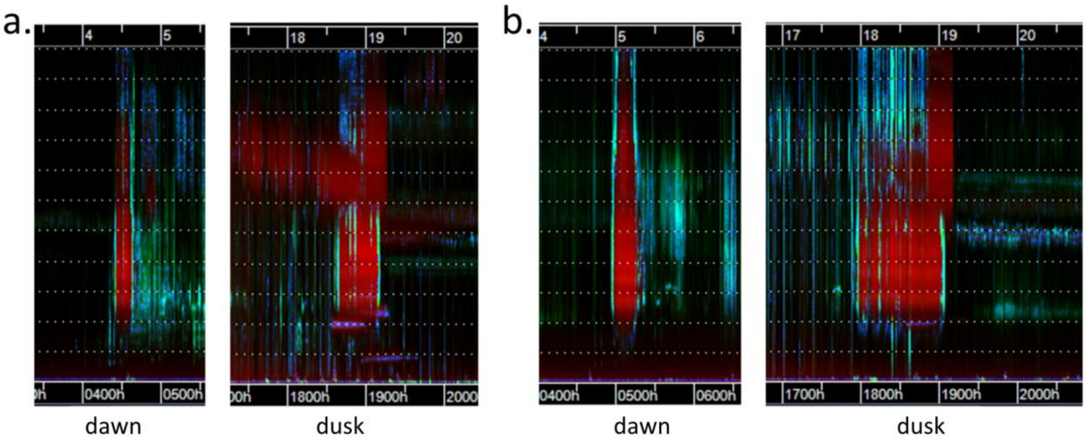


Figure 10.1a. A two and a three hour section of the BGNsp-POWsp-SPTsp false-colour spectrogram showing dawn and dusk cicada choruses at Gympie National Park on the 23 December 2015. b. A two and four hour section of the BGNsp-POWsp-SPTsp false-colour spectrogram showing the dawn and dusk choruses of the Razor Grinder Cicada (*Henicopsaltria eydouxii)* at Woondum National Park on the 9 February 2016. The frequency range is 0 to 11 kHz.

The difference in appearance of the first and last minutes of the cicada chorus may indicate there is a difference in the cicada call during these minutes. The calling parameters of another cicada, the Australian Bladder Cicada (*Cystosoma saundersii*) are known to change during the first minutes of calling (Josephson & Young, 1979). An examination of the cluster list reveals the main part of the chorus corresponds to cluster 44 and the minutes before and after the cluster 44 sequence is either cluster 12 or cluster 34.

The total number of minutes in the three clusters (44, 12, and 34) in relation to civil-dawn or civil dusk for the months of November 2015 to March 2016 is shown in Figures 10.2 and 10.3. Figure 10.2 indicates that cluster 34 occurs at the beginning and end of the *cicada dawn chorus*. Figure 10.3 in contrast indicates that cluster 12 occurs at the beginning and end of the *cicada dusk chorus*.

The clusters were examined in relation to civil dawn and civil dusk, the time when the sun is six degrees below the horizon. This time was chosen because the PCA Diel plots (Figures 6.4 to 6.7) had demonstrated the relationship between the civil dawn and the timing of the bird and cicada choruses. Civil dawn is frequently used as a reference point in research (Davis, 1958; Stehelin & Lein, 2014; Thomas et al., 2002), however sunrise is also used (Jahn et al., 2017; Keast, 1994).

The patterns in Figure 10.1 indicate that the cicada chorus at dusk is usually longer than the chorus at dawn. At dawn, the peak in the calling is very close to civil-dawn. At dusk, the peak occurs approximately equidistant from sunset and civil-dusk. There is also a clear difference in the patterns of clusters 12 and 34. Cluster 12 occurs mostly during dusk (Table 10.1).

Cluster 12 appears to be associated with an increase in BGNsp (red in Figure 10.1) in the frequencies above 6 kHz. This corresponds to the calling of the Brown Bunyip cicada (*Tamasa tristigma*) another cicada species. Cluster 34 occurs during both the dawn and dusk choruses, however apart from November 2015 and March 2016 it occurs more during the dawn chorus (see Table 10.1). The converse is true for cluster 12, which mostly occurs during dusk across each month.

Figure 10.4 shows the composite false-colour spectrogram and radar plot for clusters 12 and 34. A comparison of the composite false-colour spectrograms and radar plots of the three clusters (Figures 10.4, 8.6a and 8.14e) indicates that cluster 44 has the highest ACT acoustic index value followed by cluster 34. High ACT values indicate the sounds are reasonably continuous. Cluster 12 has lower ACT values indicating more intermittent sounds.

Table 10.1 The total number of minutes in clusters 44, 34, and 12 at each recording site during the 35 minutes before and after civil-dawn or civil-dusk. The bold indicates the highest number of minutes occurring in each cluster at each site per month.

Cluster	Month	Dawn		Dusk		In summary
		Gympie National Park	Woondum National Park	Gympie National Park	Woondum National Park	
44	November 2015	78	49	**198**	**87**	Cluster 44 occurs at dawn and dusk but more at dusk
	December 2015	200	106	**556**	**437**	
	January 2016	216	171	**430**	**509**	
	February 2016	246	424	**247**	**689**	
	March 2016	49	375	**61**	**506**	
34	November 2015	**43**	16	31	**47**	Cluster 34 occurs mostly at dawn
	December 2015	**69**	**65**	25	23	
	January 2016	**106**	**70**	76	32	
	February 2016	**91**	**68**	69	11	
	March 2016	51	96	**98**	**143**	
12	November 2015	6	0	**35**	**23**	Cluster 12 occurs mostly at dusk
	December 2015	9	7	**126**	**152**	
	January 2016	5	2	**85**	**117**	
	February 2016	12	7	**126**	**63**	
	March 2016	6	6	**58**	**18**	

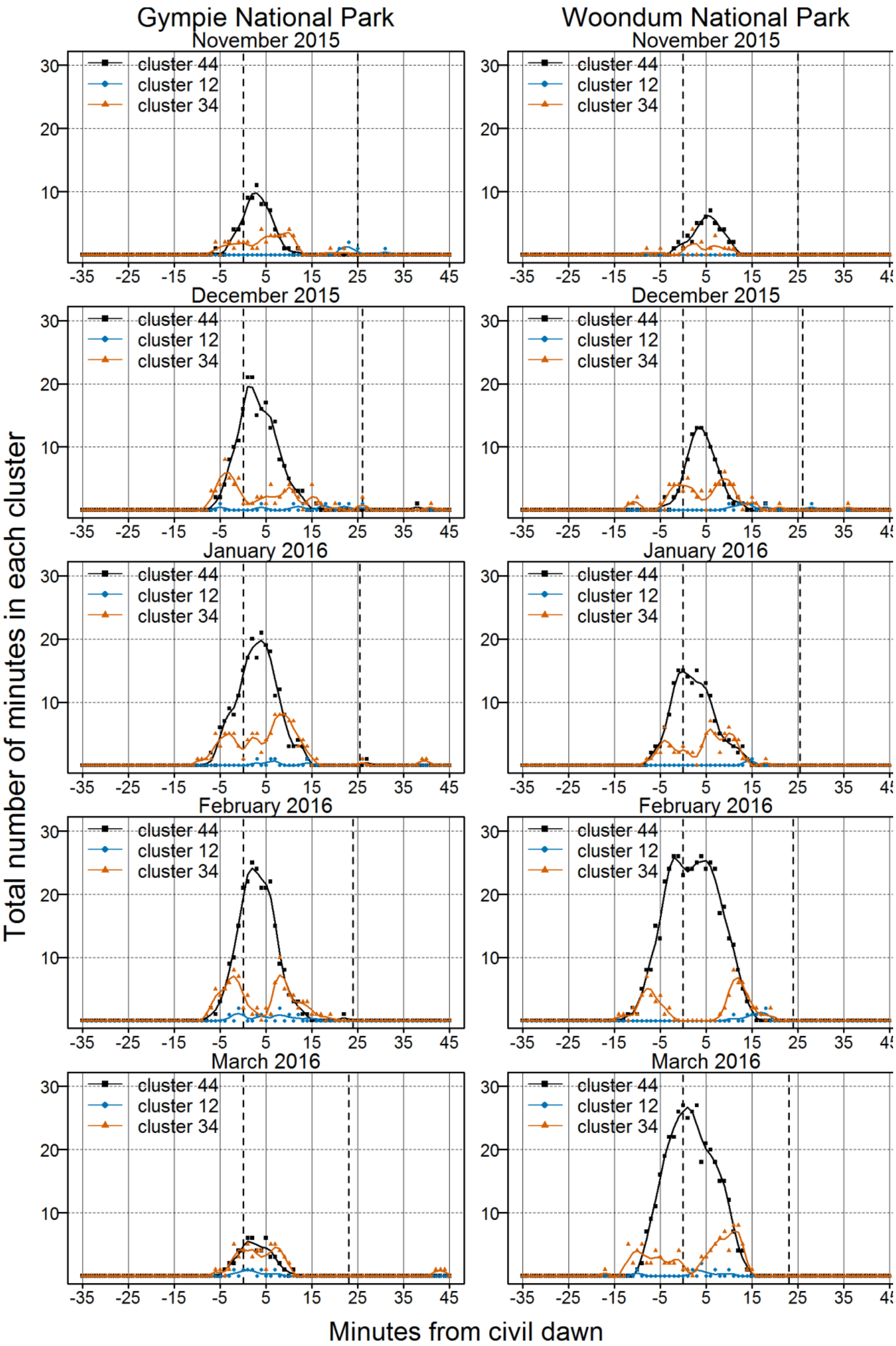


Figure 10.2 The total number of minutes in clusters 44, 12 and 34 cicada clusters relative to *civil-dawn* for the months from November 2015 to March 2016. The dotted black lines represent civil-dawn and sunrise on the 15th day of these months.

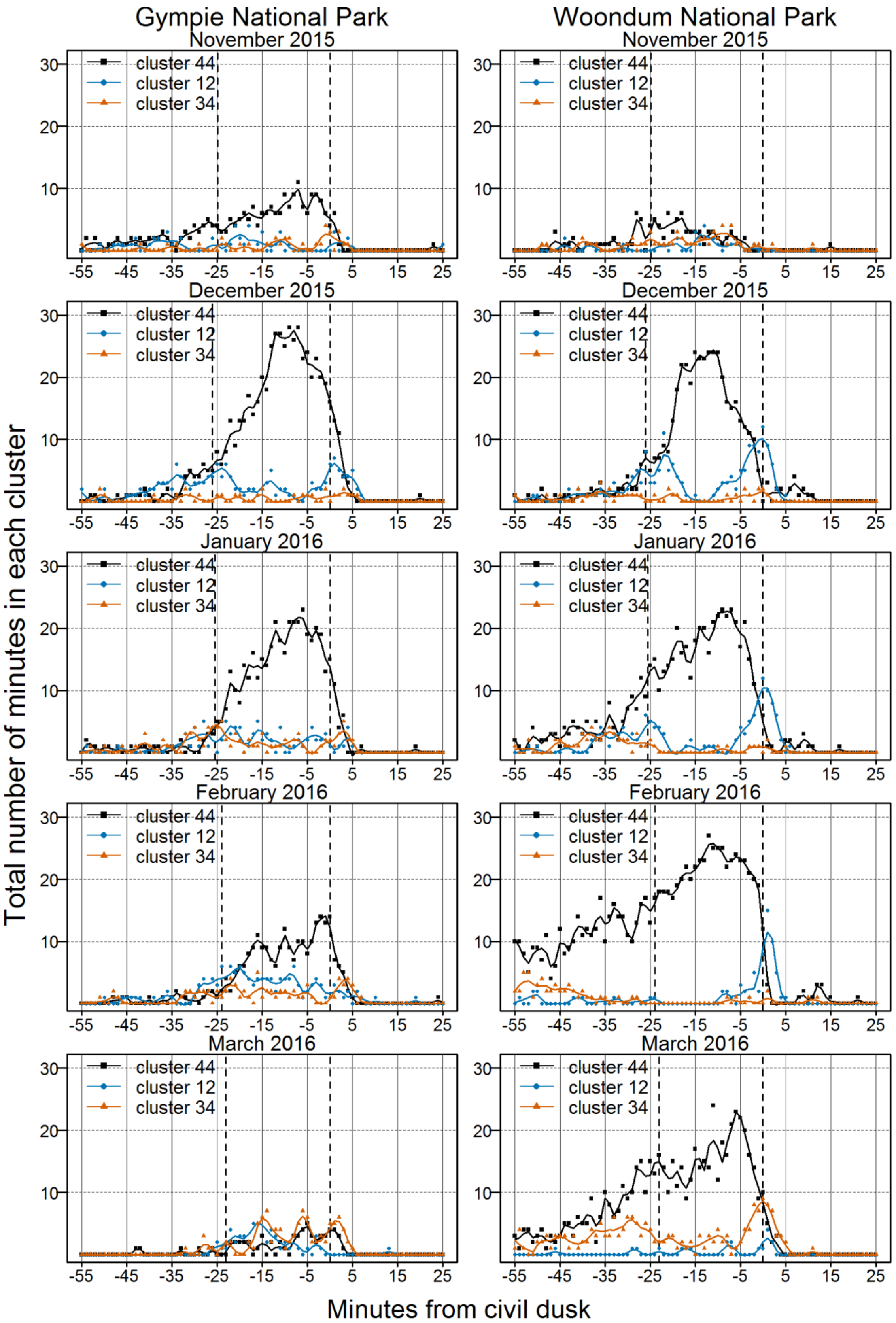


Figure 10.3 The total number of minutes in clusters 44, 12 and 34 cicada clusters relative to *civil-dusk* for the months from November 2015 to March 2016. The dotted black lines represent sunset and civil-dusk on the 15th day of these months.

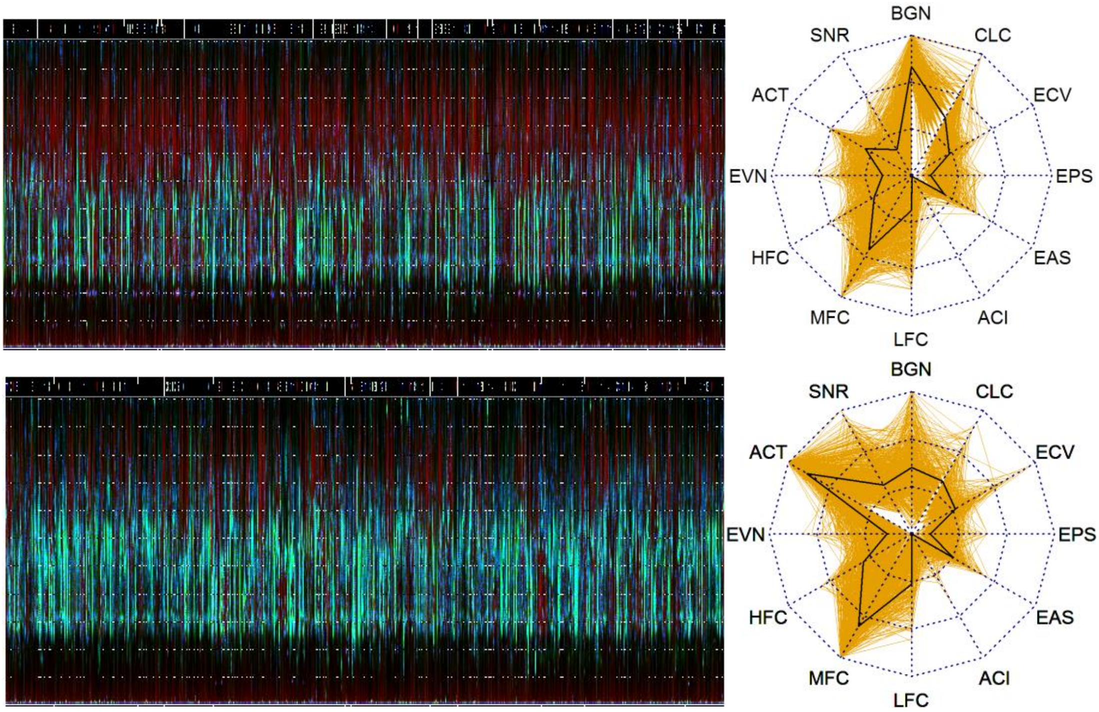


Figure 10.4 The BGNsp-POWsp-SPTsp Composite false-colour spectrogram and radar plot of cluster 12 (top) and cluster 34 (bottom).

It should be noted that the dusk period is shared by different cicada species including the Razor Grinder Cicada (*Henicopsaltria eydouxii),* Large Bottle Cicada (*Glaucopsaltria viridis*), Bladder Cicada (Cystosoma saundersii) and the Brown Bunyip Cicada (*Tamasa tristigma)*, see Appendix B. These species are common to each of the recording sites. The Large Bottle Cicada often corresponds or slightly precedes the calling of the Razor Grinder Cicada. Its call is visible in Figure 10.1a dusk image at 2 kHz.

Although it was thought that the patterns in the clusters may indicate a difference in calling parameters similar to those described in the Australian Bladder Cicada (Josephson & Young, 1979), the Razor Grinder cicada may instead be calling more intermittently during the first and last minutes. The corresponding calling of the Brown Bunyip cicada during dusk possibly results in cluster 34 being more frequent during this time. The results indicate that clustering is effective at detecting cicada choruses and is sensitive to detect small changes in these choruses.

10.3 CASE STUDY 2: THE STRUCTURE OF THE BIRD MORNING CHORUS

This study was conducted using 56 days of acoustic recordings from the Gympie National Park site from midnight to 6:45 am (from the 22 June 2015 and 16 August 2015). The birdcalls of prominently calling birds were annotated for this period. The numbers of annotations are used to display the patterns of calling of the species in relation to civil dawn.

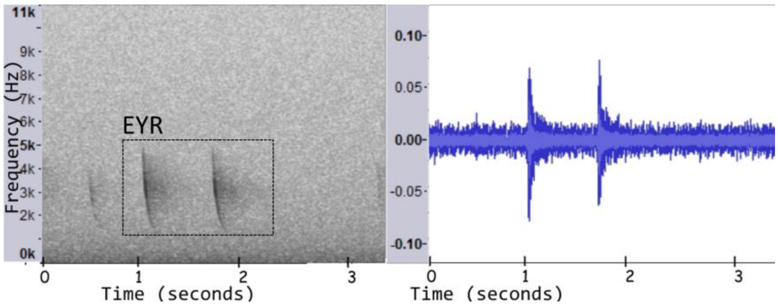
These patterns are then compared to the bird clusters from the acoustic class sequence in order to understand the structure of the bird morning chorus.

The aim of this case study was to answer two questions: 1. Does the clustering divide bird calls into species or groups of species? and 2. Can the clustering reveal the structure of the dawn chorus?

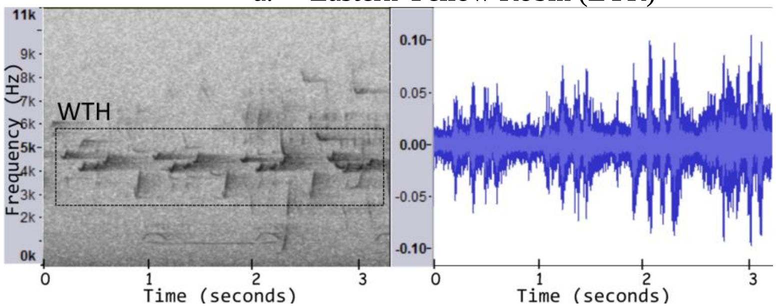
The number of calls made by the most prominently calling bird species at the Gympie National Park site was counted. The list of prominently calling bird species was determined from a survey of bird species taken from two fine days per month across the year (from July 2015 to June 2016) during the dawn period. Twenty-four minutes were sampled from the period between 25 minutes before and after civil-dawn and the numbers of calls of each species were counted. A prominently calling bird species was defined as one with a total call count in this initial survey in excess of 200 calls. The five most prominently calling bird species were the Eastern Yellow Robin (EYR), White-throated Honeyeater (WTH), Scarlet Honeyeater (SC1 & SC2), White-throated Treecreeper (WTT), and the Eastern Whipbird (EWB). An additional species, the Laughing Kookaburra (LKB) was also included due to its long, loud, broadband call, there was a count of 72 calls. The LKB call is usually a chorus of two or more birds calling in unison lasting around 30 seconds. The spectrogram and waveform of calls of each species is provided in Figure 10.5. Note that two different calls of the Scarlet Honeyeater were monitored. Of these species, the Scarlet Honeyeater is the only nomadic species; all the others are sedentary.

Kaleidoscope (Wildlife Acoustics, 2017) was used to determine sound events in the 56 day morning survey. Kaleidoscope uses Hidden Markov Models built on the clustered discrete cosine coefficients extracted from audio event segments. Fisher scores are used to determine the similarity of sound events, which is used to group the events (Wildlife Acoustics, 2017). The default parameters for this version of the program were used. These were: frequency = 0.5–10.5 kHz; duration of event = 0.1 to 7.5 seconds; inter-syllable gap = 0.35 seconds; maximum clusters = 500 and the maximum distance = 0.5.

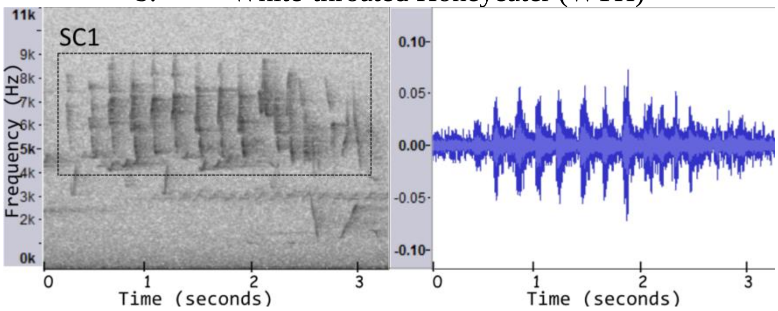
All sound events containing the six prominently calling species were annotated. These calls were also labelled according to amplitude, in the Kaleidoscope Viewer. Calls with a relative amplitude below 1000 were labelled ‘far’, between 1000 and 2000 ‘moderate’ and above 2000 ‘near’. The ‘near’ calls were loud and contained more call structure than the calls labelled ‘far’ and ‘moderate’. The amplitude levels used for the Laughing Kookaburra call were revised because of the loudness of these calls. The amplitude limits were adjusted to 2000 and 6000, that is, calls of the Laughing Kookaburra below 2000 were labelled ‘far’ and calls above 6000 were ‘near’.



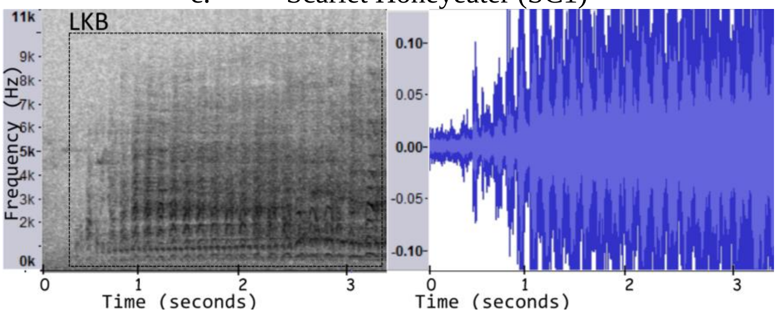
a. Eastern Yellow Robin (EYR)



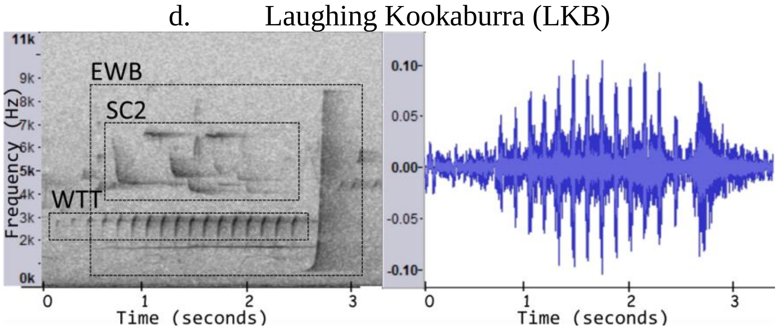
b. White-throated Honeyeater (WTH)



c. Scarlet Honeyeater (SC1)



d. Laughing Kookaburra (LKB)



e. Scarlet Honeyeater (SC2), White-throated Treecreeper (WTT) and the Eastern Whipbird (EWB)

Figure 10.5 The grey-scale spectrogram and the corresponding waveform of the birdcalls as indicated in the title below each. Note the much louder call of the Laughing Kookaburra. These images were produced using Audacity (Ash et al., 2017)

The parameter settings for the ‘inter-syllable gap’ and ‘duration of the event’ in Kaleidoscope meant that some calls were automatically split into two or more events. For example, Kaleidoscope split the two-syllable call of the Eastern Yellow Robin (Figure 10.5a) into two separate events 71% of the time. Fragmentation is encountered in automatic event detection (Brandes et al., 2006; Morfi & Stowell, 2017) due to the low amplitude gaps between call elements. The automatic event detector recognises the gaps as a break in the call and identifies call elements as separate calls. Lengthening the inter-syllable gap may have solved this problem but it would most likely have caused other problems such as increasing the complexity of event labelling, so the default settings were left unchanged.

The number of calls of each species relative to civil dawn across the 56 mornings is displayed in Figure 10.6. Each bird species joins the dawn chorus at different times. The earlier callers are the Eastern Yellow Robin, the Laughing Kookaburra followed by the White-throated Honeyeater, Eastern Whipbird and the White-throated Treecreeper. The ground-truth assists interpretation of the structure of the dawn chorus as obtained from the acoustic state clustering.

The total number of minutes relative to civil dawn of the four most common bird clusters across the 56-day survey is shown in Figure 10.7. Cluster 58 is shown separately below due to its relatively low numbers. This plot reveals a three-part structure to the dawn chorus.

When compared to the ground-truth shown in Figure 10.6 the correspondence between the plots can be made. The early morning calls of the Eastern Yellow Robin correspond with cluster 15. Cluster 37 captures the main part of the dawn chorus with eighty-three (83%) percent of the Scarlet Honeyeater SH1 calls in this cluster, along with a large proportion (34%) of the quiet calls of the Laughing Kookaburra and a higher percentage of the near and moderate calls of all species except for the Laughing Kookaburra and Eastern Yellow Robin. This indicates that cluster 37 is capturing a high rate of bird calls during the dawn chorus, but is excluding the minutes containing the louder Laughing Kookaburra calls. Cluster 11 corresponds with the latter part of the dawn chorus when the call rate is lower.

The distribution of cluster 58 (Figure 10.7) and the number of calls of the Laughing Kookaburra (Figure 10.6c) is very similar. In fact, ninety-one (91%) percent of the moderate and near Laughing Kookaburra calls clustered into cluster 58. It is clear from the results that the clustering appears to cluster on the rate of calls rather than species. However in the case of the loud and moderate calls of the Laughing Kookaburra, these were separated by the clustering along the lines of species. The clustering also reveals the structure of the dawn chorus by detecting the differences in the calling rate across the civil-dawn to sunrise period revealing a three-part dawn chorus.

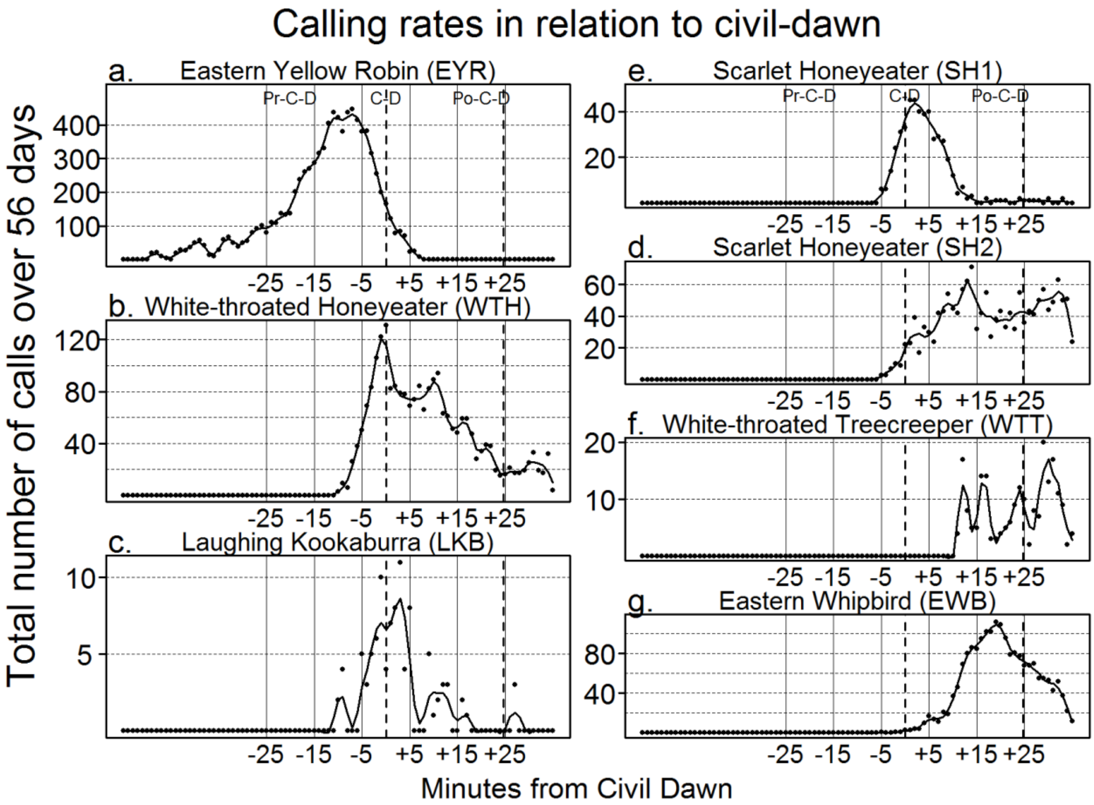


Figure 10.6 The total number of calls of each species relative to civil-dawn across the 56-day morning survey. The vertical dotted lines are civil dawn and sunrise. The Eastern Yellow Robin calls before civil dawn and the Eastern whipbird calls after civil dawn. The other species commence calling around civil-dawn. Note the different scales on the plots. Pr-C-D is pre-civil-dawn, C-D is Civil dawn, and Po-C-D is post-civil-dawn.

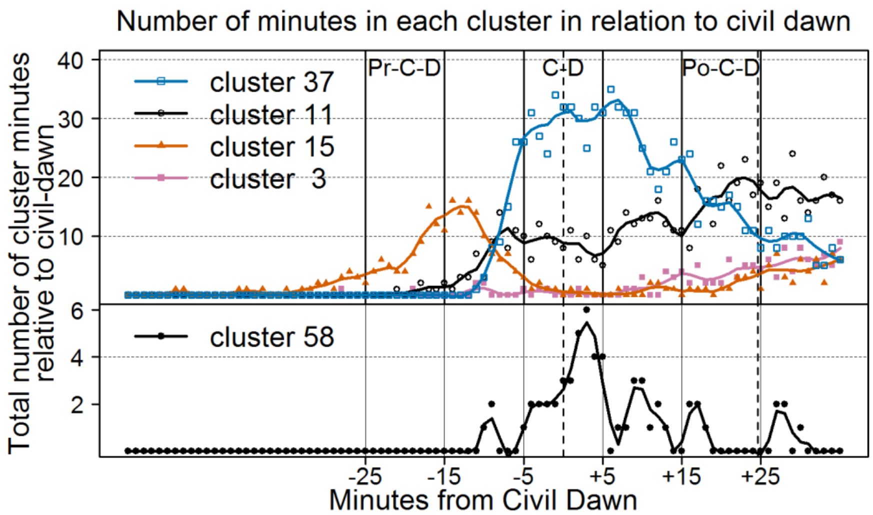


Figure 10.7 The total number of minutes in five bird clusters in each minute relative to civil-dawn across the 56-day survey at the Gympie National Park site.

10.4 CASE STUDY 3: THE INFLUENCE OF RAINFALL ON THE VOCALISATIONS OF INSECTS

This study was conducted using 24-hour totals of all moderate and heavy rain clusters and orthopteran clusters for the months of July 2015 to September 2015. A cross-correlation between the 24-hour totals were used to determine whether a positive correlation exists been the rain and orthoptera acoustic classes.

This case study was prompted by the polar histograms (Figure 9.3), which display what seems to be an association between the rain and orthopteran acoustic states. Ribbon plots also display the increase in orthopteran calling following rain (see Figure 10.8). This association was investigated through cross-correlation to determine time-delays between the rain acoustic states and the orthopteran acoustic states within a 24-hour period across the months of July to September 2015.

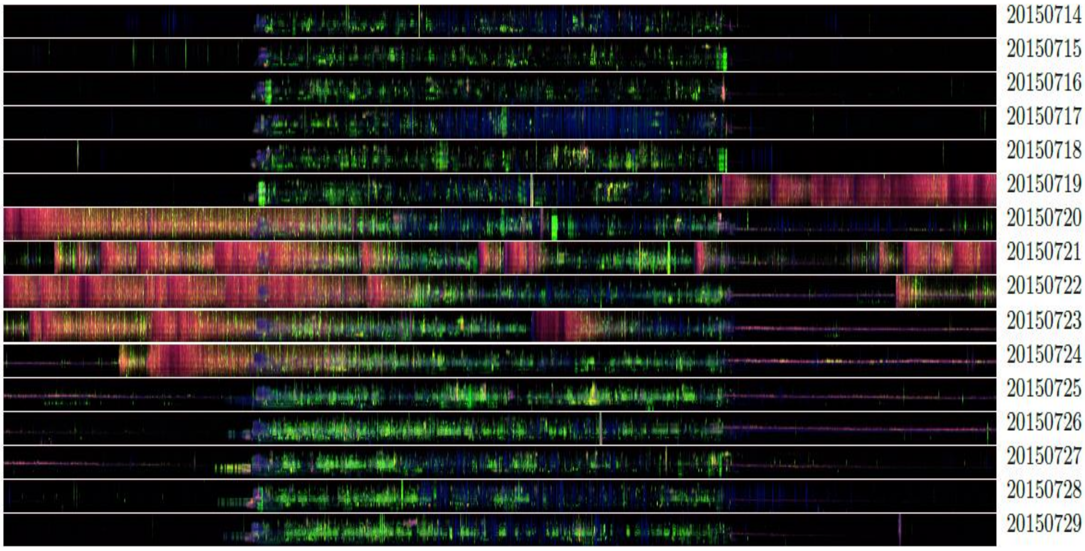


Figure 10.8 The ribbon plot from Woondum National Park showing the occurrence of rain on the 19 July 19 2015 until the 24 July 2015 followed by the occurrence of orthoptera calls. Notice the nights prior to the rain are quiet. The orthoptera calls continue between the 22 July 2015 and the morning of the 27 July 2015. After the 27 July 2015, the nights return to quiet.

All moderate and heavy rain clusters (10, 18, 21, and 59) along with the orthopteran clusters (1, 26, 27, and 29) were used to investigate the correlation between these two acoustic states. Figure 10.9 provides a histogram of the 24-hour totals of the rain and orthopteran clusters and the cross-correlation of these totals for the months of July to September 2015 at the Gympie National Park site. Figure 10.10 provides the corresponding detail for the Woondum National Park site. A positive correlation between the rain and orthopteran acoustic classes with a lag of between 0 and 1 day at the Gympie National Park site (Figure 10.9b) is evident because the cross correlations exceed the 95% confidence interval (shown as a dotted line). A positive correlation also exists at the Woondum National Park site between the rain and orthopteran acoustic classes with a lag of between 1 and 5 days (Figure 10.10b).

The increase in cricket calling intensity following rain has been observed in crickets (Key, 1970 p.337) and mole crickets (Forrest, 1983, p.196) and calling is correlated with soil moisture (Forrest, 1991). The number of eggs laid by crickets is also correlated with soil moisture (de Farias-Martins et al., 2017).

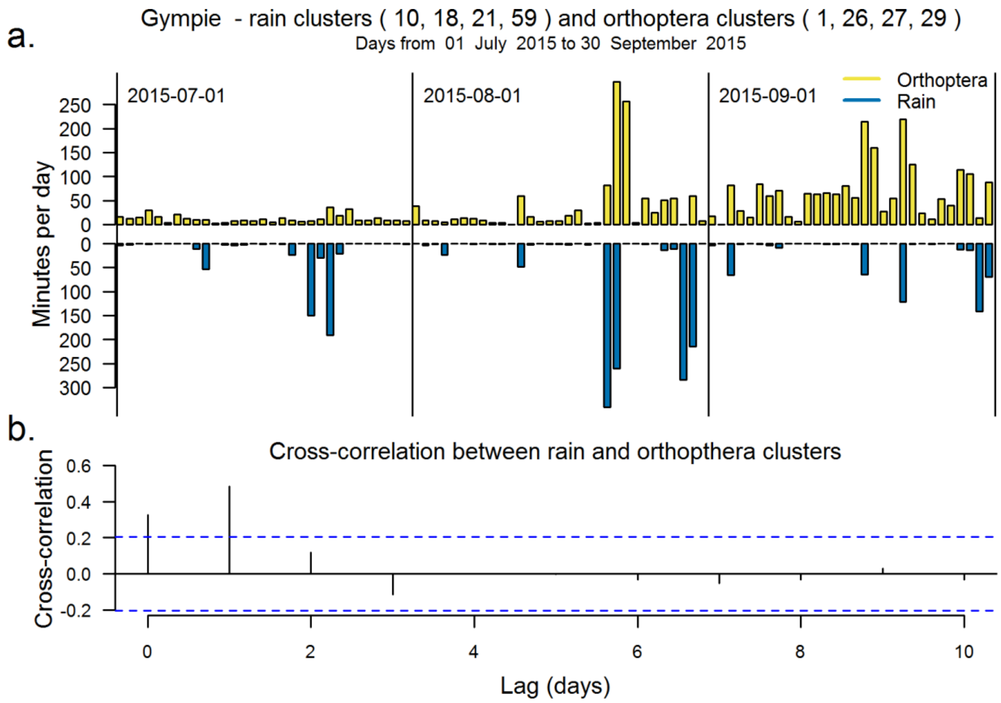


Figure 10.9a The distribution of rain and orthopteran clusters from the 1 July 2015 to 30 September 2015 at the Gympie National Park site. b. The cross-correlation shows a lag of 0 to 1 days between the rain and the orthopteran calls during these months. The blue horizontal dotted line in plot b indicates the 95% confidence interval (±1.96/√d where d is 92 days). Source: Phillips et al. (2018) https://doi.org/10.1371/journal.pone.0193345.g011.

.

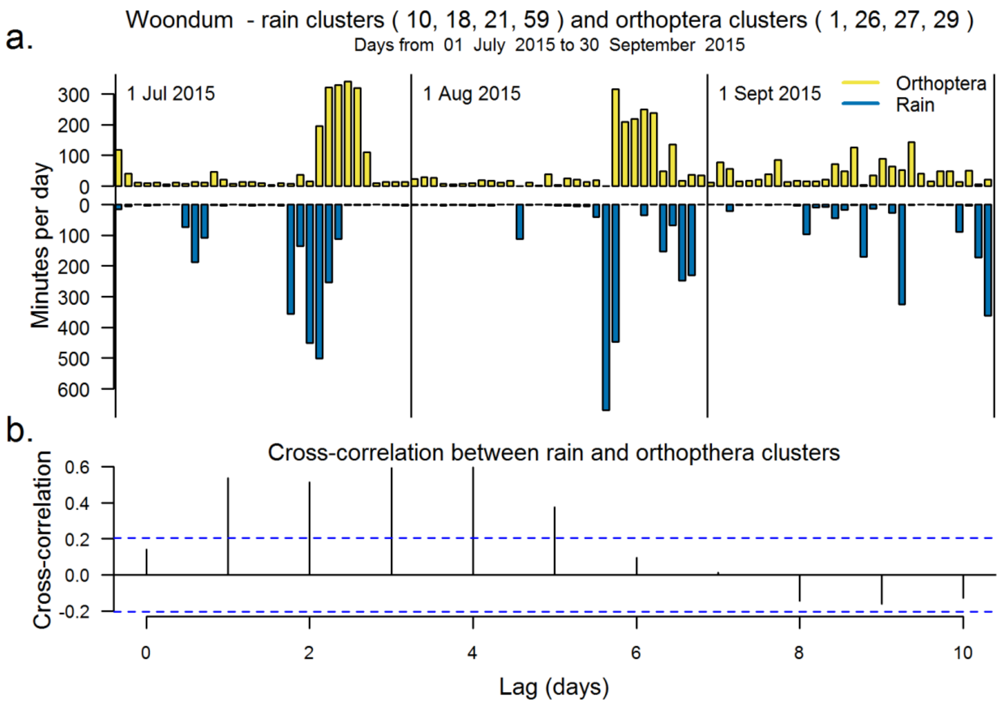


Figure 10.10a. The distribution of rain and orthopteran clusters from 1 July 2015 to the 30 September 2015 at the Woondum National Park site. b. The cross-correlation indicates a lag of 1 to 5 days between the rain and the orthopteran calls. The dotted blue horizontal lines mark the 95% confidence interval ($\pm 1.96/\sqrt{d}$ where d is 92 days). Note the different scale for the number of minutes on plot 10.10a compared to plot 10.9a.

10.5 CASE STUDY 4: THE INFLUENCE OF MOON PHASE ON THE CLUSTERS

This study was conducted using 24-hour totals of all 60 clusters across the Gympie and Woondum National Park sites separately and moon phase data obtained from the U.S. Naval Observatory (USNO) (2017). The average of the 24-hour totals for each moon phase was used to determine significant differences in the cluster occurrence across the moon phases.

This case study investigates significant differences across the clusters corresponding to moon phases. Moon phase is associated with different behaviour or calling in birds (Brigham, Gutsell, Wiacek & Geiser, 1999; Bruni, Mennill & Foote, 2014; Cooper, 1981; York, Young & Radford, 2014), amphibians (Grant, Chadwick & Halliday, 2009), insects (Steinbauer, Haslem & Edwards, 2012) and mammals (Rocha, Ferreira, Venticinque, Rodrigues & Sousa-Lima, 2017).

The moon phases in this study were converted from universal time to local time and the midpoints between the four phases were used to label the moon phases using a method similar the one used by Bruni et al. (2014).

The average of the 24-hour totals within each moon phase of each of the sixty clusters across the thirteen-month dataset from each site were tested for significant differences. Cluster 13 and 41 had significant differences across the moon phases across the thirteen months at the Gympie National Park site (Kruskal-Wallis χ^2 = 14.663 and 9.321; df = 3, p = 0.00213 and 0.02532 respectively). Figure 10.11 compares the average number of minutes per day during each moon phase and provides the radar plot of the medoids of each acoustic index in clusters 13 and 41.

Cluster 41, the quietest of the quiet clusters occurs mostly at the Gympie National Park. It has a low average number of minutes during full moon compared to the new moon. Cluster 13, the largest of all clusters (see Appendix D) instead occurs more during the full moon and a lower average during new moon. These patterns indicate that moon phase has a significant effect on the night-time soundscape.

The radar plots in Figure 10.11 indicate the soundscapes in these clusters have fundamental differences. Each cluster has high EPS values, which indicates the clusters are quiet. Cluster 41 has very low values for the other acoustic indices. Cluster 13 also has moderately high values for EAS, this indicates there is a tendency for the concentration of the acoustic energy into a very specific frequency band across each of the one-minute segments. This is most likely due to distant insect sounds. EAS is calculated in the frequency range of 1-8 kHz, this rules out the sound of aircraft on this index. Insects have been shown to be affected by moon phase (Corbet, Sellick & Willoughby, 1974; Steinbauer et al., 2012).

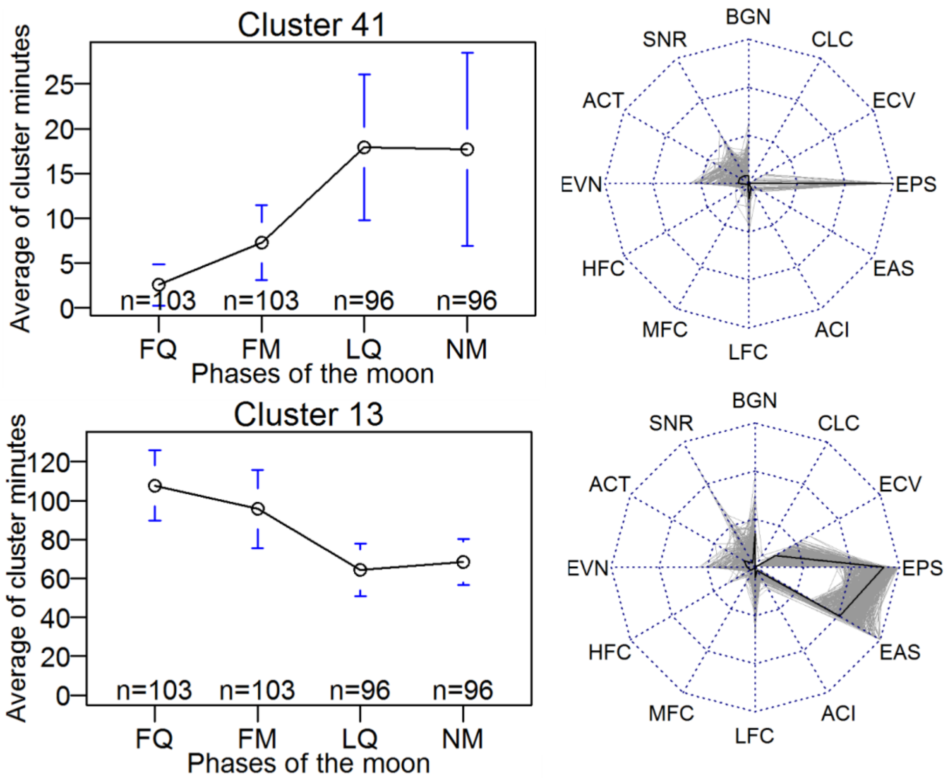


Figure 10.11 The average number of cluster minutes in clusters 6, 13, 38 and 41 at Gympie National Park during each moon phase. FQ first quarter; FM full moon; LQ last quarter; NM new moon.

Appendix C provides an analysis of the wildlife camera video footage taken from the recording sites during 2016. The two species most often captured were the Australian Brush-turkey (*Alectura lantami*) and the Swamp Wallaby (*Wallabia bicolor*). These species feed at dusk and at night and their foraging creates sounds that would be recorded. Despite the fact that most of the captures occurred during the brightest moon phases (first quarter and full moon), no conclusions can be drawn in relation to moon phase because there were breaks in the recording and most of these breaks occurred during the Last Quarter moon phase. However, the video did show that most the species recorded foraged at dusk, at night or during dawn.

10.6 CASE STUDY 5: EVIDENCE OF ANTHROPOGENIC CYCLES

This case study was conducted using 24-hour totals of all 60 clusters across the Gympie and Woondum National Park sites separately. The average of the 24-hour totals for each day of the week (Sunday to Saturday) was used to determine significant differences in the cluster occurrence across the week day.

Unlike daily and seasonal cycles, weekly cycles are not expected in natural environments. In this case study, an auto-correlation was conducted on each twenty-four hour total in each cluster at each site.

A seven-day cycle was found in Cluster 39, a cluster given the label birds and aircraft. This cluster occurs predominantly (86%) at the Gympie National Park site. The seven-day cycle (Figure 10.12) was found across all 398 days. It is not exactly clear what is causing this cycle but the presence of aircraft in this cluster is likely to be a contributing factor.

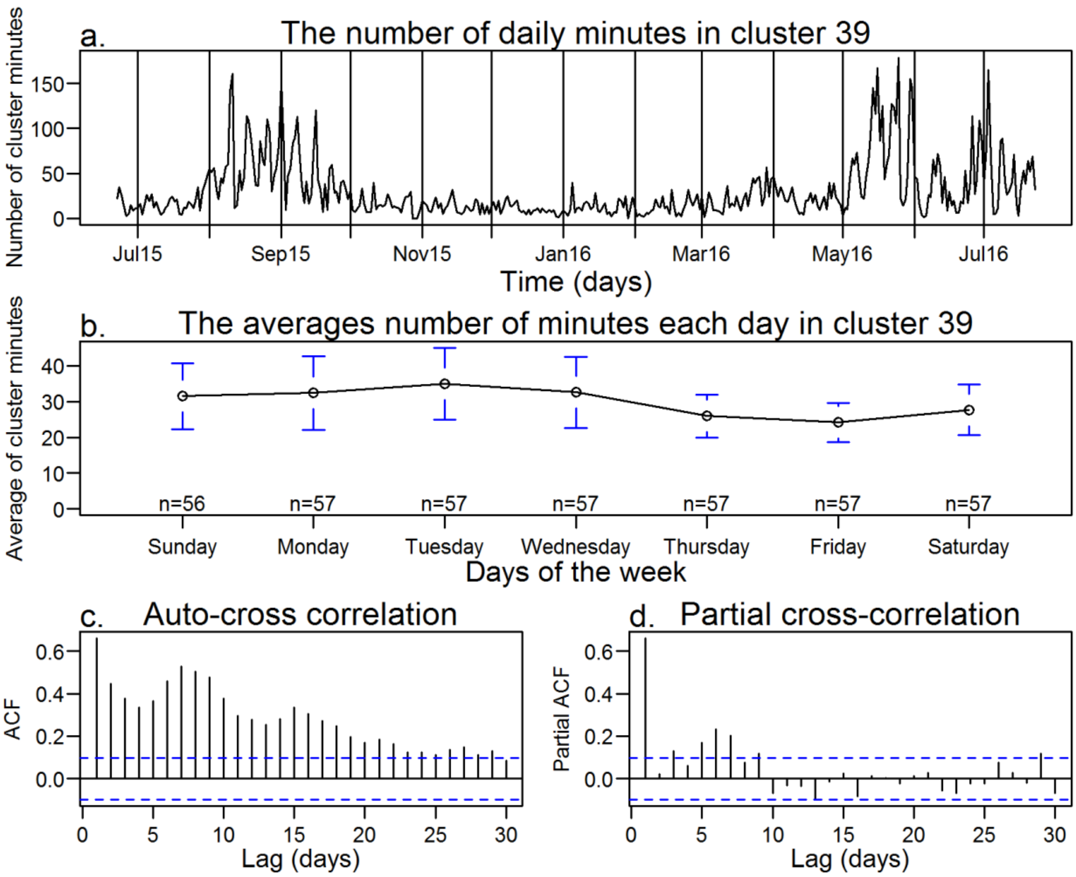


Figure 10.12a. The number of minutes in cluster 39 across the 398 days in the thirteen-month dataset. b. The average number of minutes on each day of the week with 95% confidence intervals. c. The auto-cross-correlation reveals a strong correlation at lags of 6 to 9 days. d. The partial cross-correlation of 5 to 7 days. The dotted blue horizontal lines mark the 95% confidence interval ($\pm 1.96/\sqrt{d}$ where d is 398 days).

10.7 CASE STUDY 6: CORRELATION BETWEEN TEMPERATURE AND CICADA CALLING

This case study was conducted using 24-hour totals of the cicada clusters (12, 32, 34, 44 and 48) at each site (Gympie and Woondum National Park) and the 3 pm temperatures at Gympie taken at the Bureau of Meteorology weather station (Australian Government Bureau of Meteorology, 2015). The correlation between the total time of calling within a 24-hour period and the temperature at 3 pm was examined for the days inclusive of the 1 December 2015 to the 31 March 2016.

The daily number of minutes in the cicada clusters at the two recording sites across the months of December 2015 to March 2016 is compared to the 3 pm air temperature at the Gympie weather station in Figure 10.13. Cicadas require their body temperature to be within a particular temperature range for them to sing, in most but not all cicadas this is done by basking in the sun (Sanborn & Maté, 2000; Sanborn, Villet & Phillips, 2003).

In Figure 10.13, the cicada calling time does appear to correlate with the temperature at 3 pm at the nearby weather station. The low rates of calling do appear to correspond to low 3 pm temperatures. For example, the calling is very low on the 12 December 2015. This day corresponds to rain after midday at each site, the dawn and dusk cicada choruses occur but these are reduced compared to the days that follow and there is no calling during the rain.

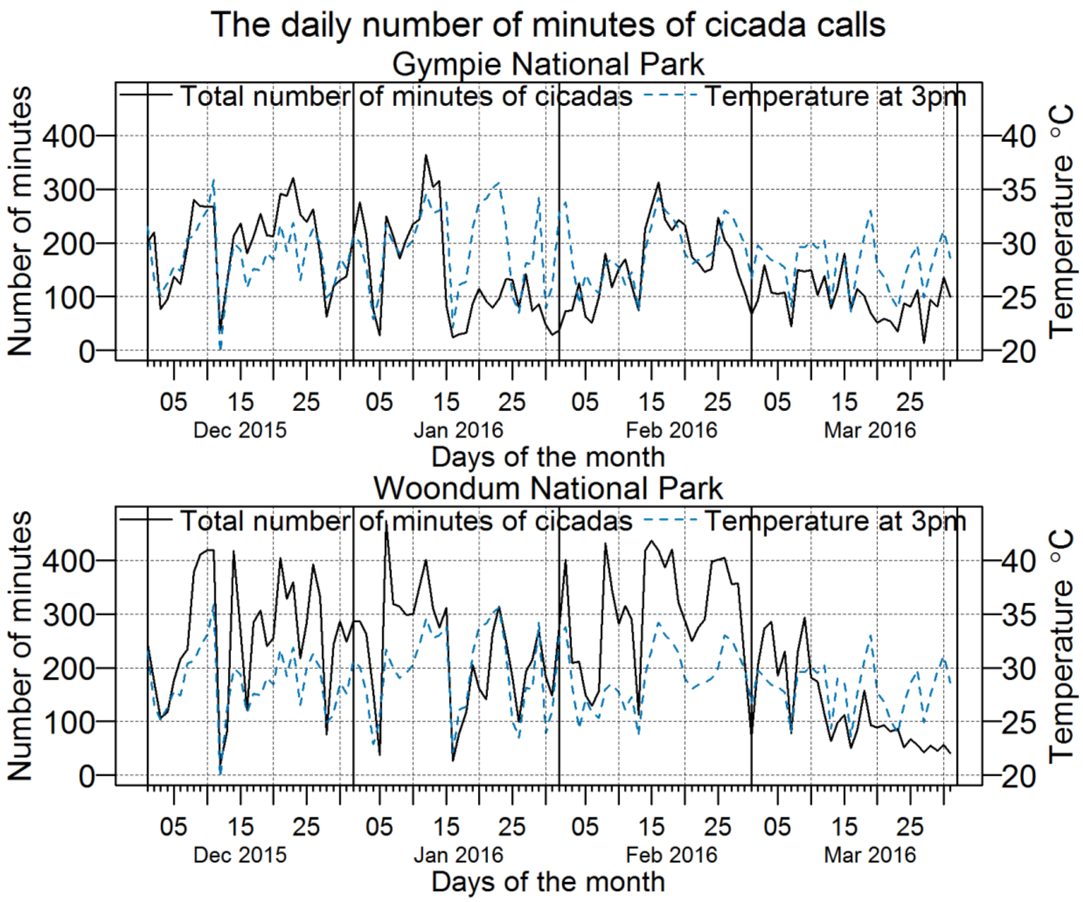


Figure 10.13 The daily totals of the number of minutes in the cicada clusters 12, 32, 34, 44 and 48 at the Gympie and Woondum National Park site. The temperature at 3 pm from the Gympie weather station is plotted in a dotted blue line.

There is a moderate positive correlation between the 3 pm air temperature and the total number of minutes of cicada calling in a twenty four hour period at the Gympie and Woondum sites (Pearson $r = 0.514$ and 0.621 respectively, $p < 0.0001$). The correlation between the twenty-four hour total number of minutes the cicadas were calling at each recordings site was high ($r = 0.734$, $p < 0.0001$). This correlation indicates correspondence in cicada calling across these sites and months and may indicate a correspondence in these soundscapes across the region.

10.8 SUMMARY

The case studies have shown how the sequence of acoustic state clusters can be used to investigate the structure of dawn and dusk choruses and the associations between acoustic classes and abiotic factors such as moon phase, rainfall and air temperature. The examination of the cluster sequence through visualisation and other methods including auto-correlation and the examination of the LDFC spectrograms and ribbon plots in relation to the cluster sequence opens up many lines of enquiry. The observation of the correspondence between the ground-truth and the clusters sequence in case studies 1, 2 and 6 provides additional verification of and confidence in the clustering method used in this research.

Chapter 11

Discussion

Continuous very-long-duration audio recordings are useful for environmental monitoring. The development of methods to access and interpret environmental recordings is of much importance in a world that relies on the continued health of our ecosystems. Very-long-duration audio recordings are becoming more common (for example see Jahn et al., 2017; Leroy, Samaran, Bonnel & Royer, 2016; Matthews, McCordic & Parks, 2014; Thomisch et al., 2016) and are predicted to play a key role in biodiversity monitoring in the future (Ganchev, 2017, p.180). However, the development of methods of analysis of very-long recordings is necessary in order to access the ecological potential in these recordings.

11.1 OVERVIEW

The aim of this thesis was to develop practical protocols and methods for the management, analysis, and visualisation of two very-long-duration audio recordings to enable ecological interpretation. The Research hypothesis was "*Clustering can provide the data reduction necessary for the visualisation of very-long-duration audio recordings to facilitate ecological interpretation and navigation*". The research hypothesis was pursued through four studies. The major contributions from the four studies are now discussed.

11.2 MAJOR CONTRIBUTIONS

11.2.1 Data Collection and Analysis Protocols

The collection of thirteen-months of audio recordings from two sites was completed using the protocol of weekly data collection and battery changes. The sampling rate of 22.05 kHz was used, to ensure that most bird, amphibian and mammal calls were recorded, these taxa mostly call in the 1-8 kHz frequency range (Napoletano, 2004 p.48; Qi et al., 2007 p.202). Although this sampling rate excludes the calls of certain cicada species (Popple, 2006) and echo locating bats, the majority of these would also not have been recorded with a sampling rate of 44.1 kHz (see Towsey et al., 2018b).

A small selection of wave files was examined which allowed the early discovery of microphone problems. A decision tree classifier was developed to detect microphone failure (Chapter 5). The files were processed using the Audio Analysis Programs (Towsey et al., 2016) on a single channel of the one-minute segments to provide the acoustic features. The use of the one-minute protocol was considered in relation to the contents and to the length of the recording. Acoustic events such as birdcalls are usually short, in the scale of seconds; however birds tend to call repeatedly. Other events such as aircraft noise, insects, and rain can span minutes or hours. In order to account for these differences and to avoid unnecessary splitting of sound events an intermediate duration was chosen. Although acoustic features can be calculated on segments in the scale of seconds when studying ambient sounds (Bormpoudakis et al., 2013); one-minute is considered an appropriate period for detecting ecoacoustic events (Farina & Salutari, 2016). A protocol was also established for listening to one-minute segments of environmental recordings allowing the identification of the soundscape elements (Section 8.3.1).

Site descriptions from recordings, government documents and on site observation were made. Eighty bird, three mammal, and eight cicada species were annotated (Chapter 3 and Appendix B). The recordings and these annotations were made publicly available via the Ecosounds website (Truskinger et al., 2014). Weather, sunrise, and sunset data was collected (Appendix A). This information was necessary for the completion of ecological investigations.

11.2.2 Data Reduction

Clustering was hypothesised as an appropriate method for data reduction because it is a widely used unsupervised learning method. Clustering had been used previously to cluster soundscapes (Bormpoudakis et al., 2013; De Coensel et al., 2008; Rychtáriková & Vermeir, 2013; Sankupellay et al., 2015; Torija et al., 2013; Yang & Kang, 2013). However, these small numbers of cases were mostly restricted to urban soundscapes and small datasets. None of the previous studies had clustered continuous very-long-duration acoustic recordings of the length of months or years.

Clustering has two inherent problems; clustering methods can be limited by the size of the dataset, and the choice of the number of clusters. The selection of the number of clusters can be problematic with high dimensional data (Lamirel, 2016). The choice of the number of clusters was resolved using the intra-three-day-distance (I3DD) error measure. The I3DD error measure, a novel contribution to this research, facilitated the choice of the clustering method.

I3DD enables cluster validation based on the ecological content in the audio recordings. This is very different to other validation methods which measure quantisation error (Gray, 1984). The I3DD error quantifies the similarity of the ecological content by comparing the acoustic signatures (Sankupellay et al., 2015) of consecutive days with the days from different seasons and sites.

The distribution of certain acoustic classes, for example heavy to light rain, is expected to be continuous. The structure imposed by clustering will not be favourable to validation methods which measure cluster separation or cluster cohesion. For this research, the advantage of the I3DD method over other cluster validation methods is therefore the reliance on acoustic signatures rather than cluster separation.

The challenge of interpreting the clusters belonging to a large acoustic dataset (1,141,147 instances) originates mainly from the fact that listening to recordings in real-time is time-consuming (Fairbrass et al., 2017; Ganchev, 2017, p.181; Kershenbaum et al., 2016). To overcome this, a combination of five methods was developed.

1. Listening to a 20-minute sample from each cluster (Section 8.3.1)
2. Examining composite false-colour spectrograms (Section 8.3.2)
3. Inspecting the time-distribution of each cluster (Section 8.3.3)
4. Studying the Sammon projection of the cluster medoids (Section 8.3.4)
5. Examining the Radar plots of cluster medoids (Section 8.3.5)

Each method provides complementary information required for the cluster evaluation. The methods include composite false-colour spectrograms. These provide the visualisation of a 10-hour sample from each cluster. These visual representations make the interpretation of the cluster contents easy. The temporal distribution plots provide evidence of the diurnal and seasonal patterns associated with bird, orthoptera, and cicada clusters, which help in reinforcing the interpretation. The radar plots illustrate which acoustic indices are contributing to each cluster. The Sammon map allows relational connections between the clusters to be examined.

The five methods rely on prior knowledge (see Figure 11.1). This knowledge informs the interpretation of the clusters, which generates new knowledge, which feeds back to inform future interpretations. This information could also indicate the need for further development of acoustic indices. The knowledge gained by the application of the five interpretation methods is something that will continue to develop with the application of this method on varied datasets.

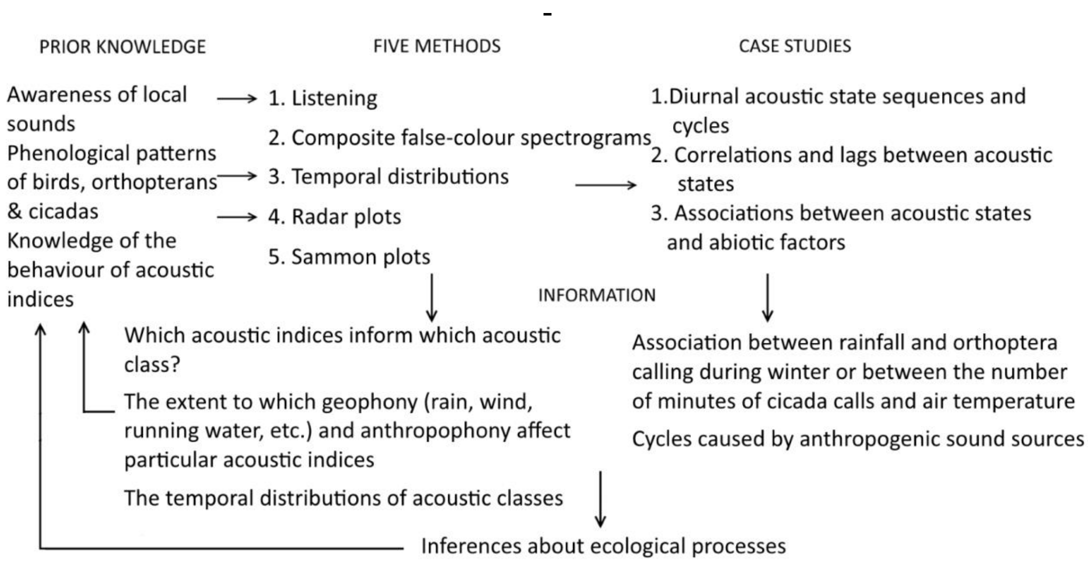


Figure 11.1: A diagram representing the relationships between the prior knowledge and the information generated by the application of the five methods used in the interpretation of the clusters and case studies used to interpret the cluster and acoustic state sequence.

11.2.3 Visualisation Techniques

Visualisation is necessary for the interpretation of audio recordings at all temporal scales (Potter, 1945; Towsey et al., 2014b) – refer to Figure 1.1. Visualisations are necessary because the human ear has difficulty detecting fine temporal structure in audio (Riede, 1998). The human eye by contrast is able to detect patterns easily (Shneiderman, 1996; Taboada-Crispi et al., 2009, p.432) and visual patterns are quickly learned to enable rapid interpretation.

Summary and spectral features were used to visualise the very-long-duration recordings. The five-visualisation techniques developed in this thesis fall into two categories, pre-clustering and post-clustering techniques. The selection and development of these techniques depends on the intended purpose. The pre-clustering techniques rely solely on the acoustic indices and can be produced immediately after feature extraction.

- Pre-clustering visualisation techniques - Ribbon plots and PCA diel plots.
- Post-clustering visualisation techniques - Dot-matrix plots, Polar Histograms and Cluster diel plots

Ribbon plots allow the visualisation of up to a month of acoustic data onto a single computer screen. This is advantageous because it allows the scanning of multiple days, enabling the identification of seasonal changes, uncharacteristic events, or associations between sound events occurring across time–scales of more than one day. These plots are versatile; they could be adjusted to a narrow frequency range if monitoring a particular species.

PCA diel plots provide a reference to the inherent acoustic structure prior to clustering. The colour-blind version clarifies the images making them more understandable to all users. As described in Phillips et al. (2018) these plots can be used for detecting microphone problems. These could be adapted to incorporate other forms of dimensionality reduction such as Independent Component Analysis (Comon, 1994; Hyvärinen & Oja, 2000).

The post-clustering visualisation techniques are dependent on the cluster results and its interpretation. Dot-matrix plots highlight the persistence and reoccurrence of acoustic states across twenty-four hours. The polar histograms show the seasonal cycling of acoustic states and could be used to monitor long-term patterns in data. Cluster diel plots map the soundscape by representing the dominant acoustic state in each minute throughout each day. The visualisations summarise the acoustic class sequence in different ways to allow the interpretation of different aspects of the data. One disadvantage of these techniques is they do not allow the display of individual clusters. This could be remedied if the plots were interactive; by clicking on a cluster element, the other elements in the cluster could be displayed. This could provide clues into the structure for example previously unobserved patterns in the orthoptera calling or nocturnal bird calls for example.

11.2.4 Ecological Interpretation

The research hypothesis was justified in various ways but particularly by the six case studies (Chapter 10). The sounds in each of the seven acoustic classes (birds, orthoptera, cicadas, wind, rain, aircraft, and quiet) were sufficiently different (Figure 11.2) allowing the clustering to find structure in the data. This thesis demonstrated that each acoustic class could be described in terms of features including the continuity, sharpness, loudness and the broadband nature of the sounds (Section 8.3.4, Figure 8.13).

The ecological interpretation of the clusters was determined by comparing cluster sequence patterns with a ground truth, each examining different aspects of ecological processes and cycles. The temporal patterns in the biophonic clusters were the first indication that ecological meaning was present in the clusters. The dawn and dusk cicada chorus and the calling of the orthoptera after rain indicate the occurrence of reproductive processes. The consistency of the diurnal patterns revealed that despite the many orders of magnitude of data reduction the clusters have an ecological interpretation. Ultimately, clustering will lead to the characterisation of audio segments using acoustic features alone, eliminating the need for human input into the verification stage of this process.

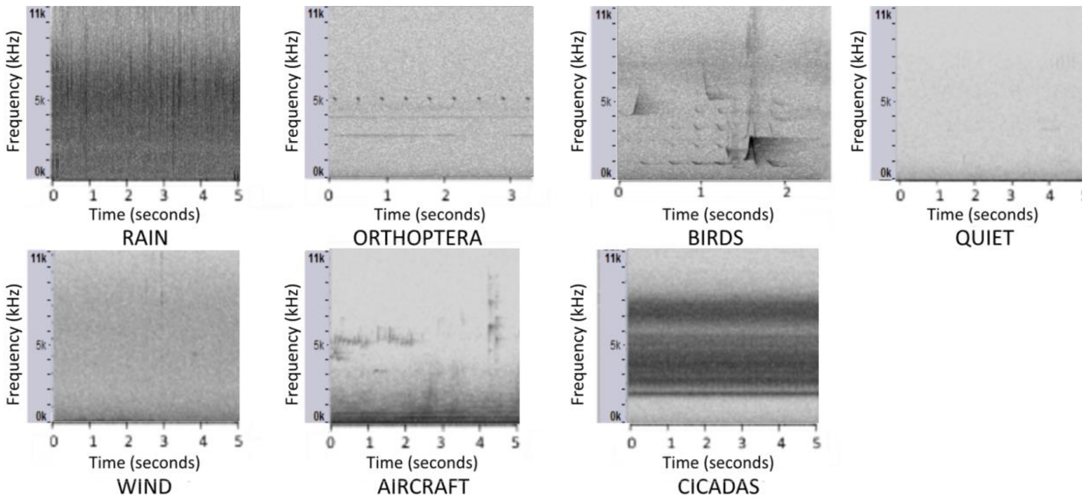


Figure 11.2 The differences in the acoustic features of the seven acoustic classes allowed clustering to separation and identification of these classes.

Zhang et al. (2016) investigated three supervised multi-label classification techniques for audio data. Supervised techniques require a labelled dataset and this is time-consuming to achieve because the labelled dataset must be large enough to reflect the distribution of acoustic events within the recording. In order to apply this technique to a very-long-duration recordings such as the one used in this research, a very large labelled dataset would have been needed. This would be time-consuming and impractical. The method of clustering outlined in this thesis does not require a labelled dataset, instead, requiring manual annotation after clustering. The expected time saving of the unsupervised method described in this thesis would be in the order of many weeks and when this is duplicated over many sites this is a considerable saving.

Using another approach also using acoustic indices, Farina et al. (2018) used an Event Detection and Identification method (Farina & Salutari, 2016) to classify one-minute recordings. This method uses the ACI index calculated across timeframes and frequency bins on one-minute audio segments (Farina et al., 2018). The method provides hundreds of distinct codes for each recording site; each code apparently represents a different combination of geophony, biophony and anthropophony. Examination of audio segments with an identical code enables the identification of the sound source represented by that code. Single codes may have an unambiguous (single interpretation) or ambiguous interpretation where different minutes in an individual code may have different interpretations, for example rain or cicadas (Farina et al., 2018). The clustering method developed in this thesis also groups some of the data ambiguously.

11.3 PRACTICAL IMPLICATIONS AND LIMITATIONS

The current method of ecological interpretation from audio recordings is either the manual or automatic annotation of all or a selected number of species or alternatively the use of a single bioacoustic metric to indicate species richness or diversity. The first method is difficult, time-consuming and requires expert knowledge (Bardeli, 2009). The second method is faster but there remain issues regarding the conclusions that can be made and currently a large amount of manual review is required to evaluate this method. This thesis has introduced an alternative, which goes some way to closing the gap between the two methods. Although this thesis does not meet the "holy-grail" of labelling species, it does increase the certainty to the conclusions drawn from the single acoustic index method. In fact, it provides a link between these two methods. It could complement the study of ecological indicators using vocalising communities instead of single species.

Apart from the demonstrated application in terrestrial forest environments, many other applications exist for this method including the study of seabird colonies (eg. Borker et al., 2014), agricultural animal feeding patterns (eg. Navon, Mizrach, Hetzroni & Ungar, 2013), sleeping disorders such as snoring (eg. Duckitt, Tuomi & Niesler, 2006), marine species (eg. Thomisch et al., 2016) and urban soundscapes (eg. Fairbrass et al., 2017). This method could also be used to provide the training data for scene detection in robotic applications (eg. Jhanwar, Sharma & Modani, 2015).

Although this research was conducted using continuous yearlong audio recordings, it could also be used to analyse recordings with other configurations. A follow-up recording was made at the two sites, a twelve-month recording consisting of three four-hour periods, one period centred on sunrise, one period centred on midday, and a third period centred on sunset. This recording could be analysed using the method described in this thesis. Weather data was also collected (Australian Government Bureau of Meteorology, 2016c, 2016d) to provide the temperature, humidity, air pressure and wind direction at half hour intervals.

The availability of the R code (Appendix A), allows this method to be reproduced on the supplied data or on a new dataset. However, three issues must be considered before implementing this method:

1. The selection of twelve days (Section 4.8.1) for the cluster optimisation may be difficult for sites that receive frequent rainfall as the method relies on the availability of days with no rain and minimal wind. An adaptation could be required to six groups of two days instead.

2. The Ecosounds website (Truskinger et al., 2014) used to listen to the sampled minutes allowed ready access to each minute. Without a platform such as this, an alternative method would be required.

3. The clusters containing more than one dominant sound source were labelled and coloured according to the source that occurred more frequently in the sample. This consideration must be kept in mind during the interpretation of the images and the cluster result.

Notwithstanding these issues, the method is adaptable and could be used with any dataset of acoustic indices. In fact, it would also be possible to have used the PCA coefficients as the acoustic features in place of the normalised summary indices. In this research, this option was not chosen because it would have been difficult to interpret the data in terms of the original acoustic indices.

The thirteen-month dataset provided has also become a valuable asset and has been used to extend research into soundscapes and sound event detection (see Kholghi, Phillips, Towsey, Sitbon & Roe, 2018; and Towsey, Roelofs, Phillips, Truskinger & Roe, 2018a).

11.4 FUTURE DIRECTIONS

The future directions are threefold: firstly, to utilise the labelled dataset produced by this research for further data mining investigations; secondly, to use the method on other datasets; and thirdly to apply the technique to other applications.

A labelled dataset such as the one produced in this research opens up many opportunities for further data mining or ecological investigation and improved categorisation and labelling of soundscapes. Further research or improvements could be conducted on aspects of the data-reduction method and visualisation techniques, these are outlined below.

1. Build the automatic detection of microphone failure/degradation into the analysis workflow.
2. The development of a method to automatically select the twelve-day dataset, eliminating the need for the manual selection of these days. Further research is also needed to understand the effect of rain on the soundscape. As seen in this research, an increase and subsequent decrease in the calling of orthoptera occurred in the days following rain during the months of July to August 2015 (winter). This information should be considered during the selection of the twelve days.
3. The development of methods to compare the consistency of the minutes in the 600-minute (or larger) sample selected for the composite false-colour spectrograms in order to understand the quality of clusters.
4. Further studies are needed to investigate the relationships between abiotic factors such as rainfall, temperature, air pressure, humidity, and moon phase and the rate of calling of different taxa. Using the rain clusters for example, studies could be designed to investigate the effect that this has on the calling rates of bird species.
5. Interactive visualisations could be made that highlight all members of a particular cluster. This would improve the understanding of the persistence of similar sounds in environmental recordings and other patterns within the acoustic sequence. Interactive visualisations would also allow scientists to focus their listening to their interests. This form of visualisation is currently under development by another researcher at the Queensland University of Technology.
6. Replicate this method on other datasets with very different soundscapes and compare the radar plots to determine the robustness of using the cluster medoids as centres for soundscape classification.

7. Apply the method to other applications in the fields of agriculture, health, robotics and marine and urban studies.

11.5 SUMMARY

The key contributions of this research included the collection of a very-long-duration audio recording, the design, and implementation of the clustering method and the optimisation of the clustering using the novel I3DD error measure, as well as the development of visualisation techniques and the evaluation of the ecological significance of the resulting clusters.

The implementation of the clustering on a continuous very-long-duration audio recording for the purpose of the interpretation of the contents had not been achieved previously. The visualisation techniques can be performed either prior to clustering using the normalised summary or spectral acoustic indices or following the clustering using the cluster result or sequence of acoustic states.

The ecological significance of the clusters was evident in both the cluster interpretation and case studies. By adding this method to the interpretation of the contents of very-long-duration audio recordings, it is hoped that it will contribute to the rapid development of ecological information and knowledge.

Bibliography

Acevedo, M. A., Corrada-Bravo, C. J., Corrada-Bravo, H., Villanueva-Rivera, L. J., & Aide, T. M. (2009). Automated classification of bird and amphibian calls using machine learning: A comparison of methods. *Ecological Informatics, 4*(4), 206–214. doi: 10.1016/j.ecoinf.2009.06.005

Agranat, I. (2010). US7782195B2 - Apparatus for scheduled low power autonomous data recording - Google Patents. Retrieved April 20, 2018, from https://patents.google.com/patent/US7782195

Aigner, W., Miksch, S., Schumann, H., & Tominski, C. (2011). Chapter 4: Visualization Aspects *Visualization of Time-Oriented Data* (pp. 69-103). London, England: Springer-Verlag London Limited.

Ames, P. L. (1971). Chapter 10 The Evolution of the Syrinx. In N. A. Ahlstrom (Ed.), *The Morphology of the Syrinx in Passerine Birds* (Vol. 37, pp. 133-152). New Haven, U.S.A.: Peabody Museum of Natural History, Yale University.

Andreopoulos, B., An, A., Wang, X., & Schroeder, M. (2008). A roadmap of clustering algorithms: finding a match for a biomedical application. *Bioinformatics, 10*(3), 297–314. doi: 10.1093/bib/bbn058

ARBIMON/Sieve Analytics. (2018). Sieve Analytics - Products. Retrieved July 6, 2018, from https://www.sieve-analytics.com/products

Ash, R., Crook, J., Dannenberg, R., Drung, B., Johnson, V., Lucius, L., & Shaw, M. (2017). Audacity: A free multi-track audio editor and recorder. from http://audacity.sourceforge.net/

Australian Government Bureau of Meteorology. (2015). Daily Weather Observations. Retrieved 7 December 2015, from http://www.bom.gov.au/climate/dwo/IDCJDW0400.shtml

Australian Government Bureau of Meteorology. (2016a). Climate statistics for Australian locations - Gympie (1981-2010). Retrieved March 15, 2016, from http://www.bom.gov.au/jsp/ncc/cdio/cvg/av?p_stn_num=040093&p_prim_element_index=0&p_comp_element_index=0&redraw=null&p_display_type=full_statistics_table&normals_years=1981-2010&tablesizebutt=normal

Australian Government Bureau of Meteorology. (2016b). Climate statistics for Australian locations - Tewantin (1981-2010). Retrieved March 15, 2016, from http://www.bom.gov.au/jsp/ncc/cdio/cvg/av?p_stn_num=040908&p_prim_element_index=0&p_comp_element_index=0&redraw=null&p_display_type=full_statistics_table&normals_years=1981-2010&tablesizebutt=normal

Australian Government Bureau of Meteorology. (2016c). Latest Weather Observations for Gympie. 2016, from http://www.bom.gov.au/products/IDQ60801/IDQ60801.94566.shtml#other_formats

Australian Government Bureau of Meteorology. (2016d). Latest Weather Observations for Tewantin. 2016, from http://www.bom.gov.au/products/IDQ60801/IDQ60801.94570.shtml

Bardeli, R. (2009). Similarity Search in Animal Sound Databases. *IEEE Transactions On Multimedia, 11*(1), 68-76. doi: 10.1109/TMM.2008.2008920

Bardeli, R., Wolff, D., Kurth, F., Koch, M., Tauchert, K.-H., & Frommolt, K.-H. (2010). Detecting bird sounds in a complex acoustic environment and application to bioacoustic monitoring. *Pattern Recognition Letters, 31*(12), 1524–1534. doi: 10.1016/j.patrec.2009.09.014

Bedoya, C., Isaza, C., Daza, J. M., & López, J. D. (2017). Automatic identification of rainfall in acoustic recordings. *Ecological Indicators, 75*, 95-100. doi: 10.1016/j.ecolind.2016.12.018

Beecher, M. D. (1988). Spectrographic Analysis of Animal Vocalizations: Implications of the "Uncertainty Principle". *Bioacoustics, 1*(2-3), 187-208. doi: 10.1080/09524622.1988.9753091

Beecher, M. D., & Brenowitz, E. A. (2005). Functional aspects of song learning in songbirds. *Trends in Ecology & Evolution, 20*(3), 143-149. doi: 10.1016/j.tree.2005.01.004

Bennett, A. F., Haslem, A., Cheal, D. C., Clarke, M. F., Jones, R. N., Koehn, J. D., . . . Yen, A. L. (2009). Ecological processes: A key element in strategies for nature conservation. *Ecological Management & Restoration, 10*(3), 192-199. doi: 10.1111/j.1442-8903.2009.00489.x

Blumstein, D. T., Mennill, D. J., Clemins, P., Girod, L., Yao, K., Patricelli, G., . . . Kirschel, A. N. G. (2011). Acoustic monitoring in terrestrial environments using microphone arrays: applications, technological considerations and prospectus. *Journal of Applied Ecology, 48*(3), 758–767. doi: 10.1111/j.1365-2664.2011.01993.x

Blumstein, D. T., & Turner, A. C. (2005). Can the acoustic adaptation hypothesis predict the structure of Australian birdsong? *Acta Ethologica, 8*(1), 35-44. doi: 10.1007/s10211-005-0107-7

Boelman, N. T., Asner, G. P., Hart, P. J., & Martin, R. E. (2007). Multi-trophic invasion resistance in Hawaii: bioacoustics, field surveys and airborne remote sensing. *Ecological Applications, 17*(8), 2137–2144. doi: 10.1890/07-0004.1

Bojkovic, Z. S., Bakmaz, B. M., & Bakmaz, M. R. (2017). Hamming Window to the Digital World. *Proceedings of the IEEE, 105*(6), 1185–1190. doi: 10.1109/jproc.2017.2697118

Boncoraglio, G., & Saino, N. (2007). Habitat Structure and the Evolution of Bird Song: a Meta-analysis of the Evidence for the Acoustic Adaptation Hypothesis. *Functional Ecology, 21*(1), 134-142. doi: 10.1111/j.1365-2435.2006.01207.x

Borker, A. L., McKown, M. W., Ackerman, J. T., Eagles-Smith, C. A., Tershy, B. R., & Croll, D. A. (2014). Vocal Activity as a Low Cost and Scalable Index of Seabird Colony Size. *Conservation Biology, 28*(4), 1100-1108. doi: 10.1111/cobi.12264

Bormpoudakis, D., Sueur, J., & Pantis, J. D. (2013). Spatial heterogeneity of ambient sound at the habitat type level: ecological implications and applications. *Landscape Ecology, 28*(3), 495–506. doi: 10.1007/s10980-013-9849-1

Brandes, T. S. (2008a). Automated sound recording and analysis techniques for bird surveys and conservation. *Bird Conservation International, 18*, S163–S173. doi: 10.1017/S0959270908000415

Brandes, T. S. (2008b). *Feature Vector Selection and Use With Hidden Markov Models to Identify Frequency-Modulated Bioacoustic Signals Amidst Noise*. Paper presented at the IEEE Transactions On Audio, Speech, And Language Processing, Las Vegas, U.S.A. doi:10.1109/tasl.2008.925872.

Brandes, T. S., Naskrecki, P., & Figueroa, H. K. (2006). Using image processing to detect and classify narrow-band cricket and frog calls. *The Journal of the Acoustical Society of America, 120*(5), 2950-2957. doi: 10.1121/1.2355479

Brewer, C., Harrower, M., & The Pennsylvania State University. (2017). ColourBrewer 2. Retrieved 28 November 2017, from http://colorbrewer2.org/#type=diverging&scheme=RdYlBu&n=11

Brigham, R. M., Gutsell, R. C. A., Wiacek, R. S., & Geiser, F. (1999). Foraging Behaviour in Relation to the Lunar Cycle by Australian Owlet-nightjars Aegotheles cristatus. *Emu - Austral Ornithology, 99*(4), 253–261. doi: 10.1071/mu99031

Brighten, A. (2015). *Vocalisations of the New Zealand morepork (Ninox novaeseelandiae) on Ponui Island.* (Master of Science in Zoology), Massey University, Palmerston North, New Zealand. Retrieved from https://mro.massey.ac.nz/handle/10179/7321

Brown, T. J., & Handford, P. (2000). Sound Design for Vocalizations: Quality in the Woods, Consistency in the Fields. *The Condor*, *102*(1), 81-92. doi: 10.2307/1370409

Bruni, A., Mennill, D. J., & Foote, J. R. (2014). Dawn chorus start time variation in a temperate bird community: relationships with seasonality, weather, and ambient light. *Journal of Ornithology, 155*(4), 877-890. doi: 10.1007/s10336-014-1071-7

Burt, J. M., & Vehrencamp, S. I. (2005). Chapter 15: Dawn chorus as an interactive communication network. In P. K. McGregor (Ed.), *Animal Communication Networks* (pp. 320-343): Cambridge University Press.

Buxton, R. T., Brown, E., Sharman, L., Gabriele, C. M., & McKenna, M. F. (2016). Using bioacoustics to examine shifts in songbird phenology. *Ecology and Evolution, 6*(14), 4697–4710. doi: 10.1002/ece3.2242

Campos-Cerqueira, M., & Aide, T. M. (2016). Improving distribution data of threatened species by combining acoustic monitoring and occupancy modelling. *Methods in Ecology and Evolution, 7*(11), 1340–1348. doi: 10.1111/2041-210x.12599

Campos-Cerqueira, M., & Aide, T. M. (2017). Changes in the acoustic structure and composition along a tropical elevational gradient. *Journal of Ecoacoustics, 1*, PNCO7I. doi: 10.22261/jea.pnco7i

Chan, A. A. Y.-H., Giraldo-Perez, P., Smith, S., & Blumstein, D. T. (2010). Anthropogenic noise affects risk assessment and attention: the distracted prey hypothesis. *Biology Letters, 6*(4), 458-461. doi: 10.1098/rsbl.2009.1081

Chen, Z., & Maher, R. C. (2006). Semi-automatic classification of bird vocalizations using spectral peak tracks. *The Journal of the Acoustical Society of America*, *120*(5), 2974-2984. doi: 10.1121/1.2345831

Christesen, L. S., & Nelson, J. (2000). Vocal communication in the Grey-headed Flying-fox Pteropus poliocephalus (Chiroptera: Pteropodidae). *Australian Zoologist, 31*(3), 447–457. doi: 10.7882/az.2000.005

Church, R. J. (1997). Avian frugivory in a subtropical rainforest: eleven years of observations in Lamington National Park. *Sunbird: Journal of the Queensland Ornithological Society, 27*(4), 85-97. Retrieved from https://search.informit.com.au/

Çiflikli, C., & Kahya-Özyirmidokuz, E. (2010). Implementing a data mining solution for enhancing carpet manufacturing productivity. *Knowledge-Based Systems, 23*(8), 783-788. doi: 10.1016/j.knosys.2010.05.001

Colbert, D. S., Ruttinger, J. A., Streich, M., Chamberlain, M., Conner, L. M., & Warren, R. J. (2015). Application of autonomous recording units to monitor gobbling activity by wild turkey. *Wildlife Society Bulletin, 39*(4), 757–763. doi: 10.1002/wsb.577

Comon, P. (1994). Independent component analysis, A new concept? *Signal Processing, 36*(3), 287-314. doi: 10.1016/0165-1684(94)90029-9

Cooley, J. W., & Tukey, J. W. (1965). An Algorithm for the Machine Calculation of Complex Fourier Series. *Mathematics of Computation, 19*(90), 297-301. doi: 10.2307/2003354

Cooper, R. J. (1981). Relative Abundance of Georgia Caprimulgids Based on Call-Counts. *The Wilson Bulletin, 93*(3), 363-371. Retrieved from http://www.jstor.org/stable/4161502.

Corbet, S. A., Sellick, R. D., & Willoughby, N. G. (1974). Notes on the biology of the mayfly Povilla adusta in West Africa. *Journal of Zoology, 172*(4), 491-502. doi: 10.1111/j.1469-7998.1974.tb04381.x

Dabelsteen, T., & Mathevon, N. (2002). Why do songbirds sing intensively at dawn? *Acta Ethologica, 4*(2), 65-72. doi: 10.1007/s10211-001-0056-8

Dale, M. (2017). Chapter 8 Temporal and Time-Only Graphs *Applying Graph Theory in Ecological Research* (pp. 164-190). Cambridge: Cambridge University Press.

Davis, J. (1958). Singing Behavior and the Gonad Cycle of the Rufous-Sided Towhee. *The Condor, 60*(5), 308-336. doi: 10.2307/1365157

De Coensel, B., Botteldooren, D., Debacq, K., Nilsson, M. E., & Berglund, B. (2007). *Soundscape classifying ants*. Paper presented at the 36th International Congress and

Exhibition on Noise Control Engineering (Inter-Noise 2007). Istanbul, Turkey. https://biblio.ugent.be/publication/394394/file/587595

De Coensel, B., Botteldooren, D., Debacq, K., Nilsson, M. E., & Berglund, B. (2008). *Clustering outdoor soundscapes using fuzzy ants*. Paper presented at the IEEE Congress on Evolutionary Computation (CEC 2008), Hong Kong, China. doi:10.1109/cec.2008.4630999.

de Farias-Martins, F., Sperber, C. F., Albeny-Simões, D., Breaux, J. A., Fianco, M., & Szinwelski, N. (2017). Forest litter crickets prefer higher substrate moisture for oviposition: Evidence from field and lab experiments. *Plos One, 12*(10), e0185800. doi: 10.1371/journal.pone.0185800

Dema, T., Zhang, L., Towsey, M., Truskinger, A., Sherub, S., Kinley, . . . Roe, P. (2017). *An Investigation into Acoustic Analysis Methods for Endangered Species Monitoring: A Case of Monitoring the Critically Endangered White-Bellied Heron in Bhutan*. Paper presented at the IEEE 13th International Conference on e-Science, Auckland, New Zealand. doi:10.1109/escience.2017.30.

Deneubourg, J. L., Goss, S., Franks, N., Sendova-Franks, A., Detrain, C., & Chrétien, L. (1991). *The dynamics of collective sorting robot-like ants and ant-like robots*. Paper presented at the 1st International Conference on Simulation of Adaptive Behavior on from animals to animats, Paris, France. http://www.ulb.ac.be/sciences/use/publications/Claire/11.pdf

Depraetere, M., Pavoine, S., Jiguet, F., Gasc, A., Duvail, S., & Sueur, J. (2012). Monitoring animal diversity using acoustic indices: Implementation in a temperate woodland. *Ecological Indicators, 13*(1), 46–54. doi: 10.1016/j.ecolind.2011.05.006

Dong, X., Towsey, M., Zhang, J., Banks, J., & Roe, P. (2013). *A novel representation of bioacoustic events for content-based search in field audio data*. Paper presented at the 2013 International Conference on Digital Image Computing: Techniques and Applications (DICTA), Hobart, Tasmania, Australia. doi:10.1109/dicta.2013.6691473.

Doolan, J. M., & Mac Nally, R. C. (1981). Spatial Dynamics and Breeding Ecology in the Cicada Cystosoma saundersii: The Interaction Between Distributions of Resources and Intraspecific Behaviour. *The Journal of Animal Ecology, 50*(3), 925-940. doi: 10.2307/4147

Dooling, R. J. (1983). Chapter 4 Auditory perception in birds In D. E. Kroodsma & E. H. Miller (Eds.), *Acoustic Communication in Birds* (pp. 95-130). New York, U.S.A.: Academic Press.

Dooling, R. J. (2004). Chapter 7 Audition: Can birds hear everything they sing? In P. R. Marler & H. Slabbekoorn (Eds.), *Nature's Music: The Science of Birdsong* (pp. 206–225). San Diego: Elsevier-Academic.

Duckitt, W. D., Tuomi, S. K., & Niesler, T. R. (2006). Automatic detection, segmentation and assessment of snoring from ambient acoustic data. *Physiological Measurement, 27*(10), 1047-1056. doi: 10.1088/0967-3334/27/10/010

Dunn, J. C. (1974). Well-Separated Clusters and Optimal Fuzzy Partitions. *Journal of Cybernetics, 4*(1), 95–104. doi: 10.1080/01969727408546059

Eglington, S. M., Noble, D. G., & Fuller, R. J. (2012). A meta-analysis of spatial relationships in species richness across taxa: Birds as indicators of wider biodiversity in temperate regions. *Journal for Nature Conservation, 20*(5), 301-309. doi: 10.1016/j.jnc.2012.07.002

Eldridge, A., Casey, M., Moscoso, P., & Peck, M. (2016). A new method for ecoacoustics? Toward the extraction and evaluation of ecologically-meaningful soundscape components using sparse coding methods. *PeerJ, 4*(6), e2108. doi: 10.7717/peerj.2108

Elemans, C. P. H., Mead, A. F., Rome, L. C., & Goller, F. (2008). Superfast Vocal Muscles Control Song Production in Songbirds. *Plos One, 3*(7), e2581. doi: 10.1371/journal.pone.0002581

Ellis, W., Bercovitch, F., FitzGibbon, S., Roe, P., Wimmer, J., Melzer, A., & Wilson, R. (2011). Koala bellows and their association with the spatial dynamics of free-ranging koalas. *Behavioral Ecology*, *22*(2), 372–377. doi: 10.1093/beheco/arq216

Ewart, A. (2005). New genera and species of small ticking and 'chirping' cicadas (Hemiptera: Cicadoidea: Cicadidae) from Queensland, with descriptions of their songs. *Memoirs of the Queensland Museum (0079-8835)*, *51*(2), 439-500.

Ewart, A., & Popple, L. W. (2007). Songs and calling behaviour of 'Froggattoides typicus' Distant (Hemiptera: Cicadoidea: Cicadidae), a nocturnally singing cicada. *Australian Entomologist*, *34*(4), 127-139.

Eyre, T. J., & Buck, R. G. (2005). The regional distribution of large gliding possums in southern Queensland, Australia. I. The yellow-bellied glider (Petaurus australis). *Biological Conservation*, *125*(1), 65-86. doi: 10.1016/j.biocon.2005.03.012

Eyre, T. J., & Goldingay, R. L. (2005). Characteristics of sap trees used by yellow-bellied gliders in southern Queensland. *Wildlife Research*, *32*(1), 23-35. doi: 10.1071/wr03075

Eyre, T. J., Kelly, A. L., Neldner, V. L., Wilson, B. A., Ferguson, D. J., Laidlaw, M. J., & Franks, A. J. (2015). *BioCondition: A Condition Assessment Framework for Terrestrial Biodiversity in Queensland. Assessment Manual. Version 2.2*. Brisbane.: Retrieved from https://www.qld.gov.au/environment/assets/documents/plants-animals/biodiversity/biocondition-assessment-manual.pdf.

Fairbrass, A. J., Rennett, P., Williams, C., Titheridge, H., & Jones, K. E. (2017). Biases of acoustic indices measuring biodiversity in urban areas. *Ecological Indicators*, *83*, 169-177. doi: 10.1016/j.ecolind.2017.07.064

Faith, D. P., Minchin, P. R., & Belbin, L. (1987). Compositional dissimilarity as a robust measure of ecological distance. *Theory and Models in Vegetation Science*, *69*(1/3), 57-68. doi: 10.1007/978-94-009-4061-1_6

Farina, A. (2018). Perspectives in ecoacoustics: A contribution to defining a discipline. *Journal of Ecoacoustics*, *2*, TRZD5I. doi: 10.22261/JEA.TRZD5I

Farina, A., Buscaino, G., Ceraulo, M., & Pieretti, N. (2014a). The soundscape approach for the assessment and conservation of mediterranean landscapes: Principles and case studies. *Journal of Landscape Ecology*, *7*(1), 10–22. doi: 10.2478/jlecol-2014-0007

Farina, A., Ceraulo, M., Bobryk, C., Pieretti, N., Quinci, E., & Lattanzi, E. (2015). Spatial and temporal variation of bird dawn chorus and successive acoustic morning activity in a Mediterranean landscape. *Bioacoustics*, *24*(3), 269–288. doi: 10.1080/09524622.2015.1070282

Farina, A., Gage, S. H., & Salutari, P. (2018). Testing the ecoacoustics event detection and identification (EEDI) approach on Mediterranean soundscapes. *Ecological Indicators*, *85*, 698–715. doi: 10.1016/j.ecolind.2017.10.073

Farina, A., James, P., Bobryk, C., Pieretti, N., Lattanzi, E., & McWilliam, J. (2014b). Low cost (audio) recording (LCR) for advancing soundscape ecology towards the conservation of sonic complexity and biodiversity in natural and urban landscapes. *Urban Ecosystems*, *17*(4), 923–944. doi: 10.1007/s11252-014-0365-0

Farina, A., & Pieretti, N. (2014). Sonic environment and vegetation structure: A methodological approach for a soundscape analysis of a Mediterranean maqui. *Ecological Informatics*, *21*, 120-132. doi: 10.1016/j.ecoinf.2013.10.008

Farina, A., Pieretti, N., & Malavasi, R. (2014c). Patterns and dynamics of (bird) soundscapes: A biosemiotic interpretation. *Semiotica*, *2014*(198), 241-255. doi: 10.1515/sem-2013-0109

Farina, A., Pieretti, N., & Piccioli, L. (2011). The soundscape methodology for long-term bird monitoring: A Mediterranean Europe case-study. *Ecological Informatics*, *6*(6), 354–363. doi: 10.1016/j.ecoinf.2011.07.004

Farina, A., Pieretti, N., Salutari, P., Tognari, E., & Lombardi, A. (2016). The Application of the Acoustic Complexity Indices (ACI) to Ecoacoustic Event Detection and Identification (EEDI) Modeling. *Biosemiotics*, *9*(2), 227-246. doi: 10.1007/s12304-016-9266-3

Farina, A., & Salutari, P. (2016). Applying the Ecoacoustic Event Detection and Identification (EEDI) Model to the Analysis of Acoustic Complexity. *Journal of Mediterranean Ecology, 14*, 13-42. Retrieved from http://www.jmecology.com/?attachment_id=444

Ferreira, L. M., Oliveira, E. G., Lopes, L. C., Brito, M. R., Baumgarten, J., Rodrigues, F. H., & Sousa-Lima, R. S. (2018). What do insects, anurans, birds, and mammals have to say about soundscape indices in a tropical savanna. *Journal of Ecoacoustics, 2*, PVH6YZ. doi: 10.22261/jea.pvh6yz

Fletcher, N. H. (2007). Chapter 19 Animal Bioacoustics. In T. D. Rossing (Ed.), *Handbook of Acoustics* (pp. 785-804). New York, U.S.A.: Springer.

Fletcher, N. H., & Hill, K. G. (1978). Acoustics of Sound Production and of Hearing in the Bladder Cicada Cystosoma saundersii (Westwood). *Journal of Experimental Biology, 72*(1), 43-55. Retrieved from http://newt.phys.unsw.edu.au/music/people/publications/Fletcheretal1978.pdf.

Forrest, T. G. (1983). Chapter 9 Calling songs and mate choice in mole crickets. In D. T. Gwynne & G. K. Morris (Eds.), *Orthopteran mating systems: sexual competition in a diverse group of insects* (pp. 185-204). Boulder, U.S.A.: Westview.

Forrest, T. G. (1991). Power output and efficiency of sound production by crickets. *Behavioral Ecology, 2*(4), 327-338. doi: 10.1093/beheco/2.4.327

Forrest, T. G. (1994). From Sender to Receiver: Propagation and Environmental Effects on Acoustic Signals. *American Zoologist, 34*(6), 644-654. doi: 10.1093/icb/34.6.644

Fraley, C. (1998). Algorithms for Model-Based Gaussian Hierarchical Clustering. *SIAM Journal on Scientific Computing, 20*(1), 270–281. doi: 10.1137/s1064827596311451

Fraley, C., & Raftery, A. E. (2002). Model-Based Clustering, Discriminant Analysis, and Density Estimation. *Journal of the American Statistical Association, 97*(458), 611-631. doi: 10.1198/016214502760047131

Fraley, C., & Raftery, A. E. (2007). Model-based Methods of Classification: Using the mclust Software in Chemometrics. *Journal of Statistical Software, 18*(6), 1-13. doi: 10.18637/jss.v018.i06

Fraley, C., Raftery, A. E., Murphy, T. E., & Scrucca, L. (2012). R package 'mclust': Version 4 for R: Normal Mixture Modeling for Model-Based Clustering. *Classification, and Density Estimation Technical Report No. 597, Department of Statistics, University of Washington. Retrieved from https://www.stat.washington.edu/sites/default/files/files/reports/2012/tr597.pdf*.

Frank, E., Hall, M. A., & Witten, I. H. (2016). *The WEKA Workbench. Online Appendix for "Data Mining: Practical Machine Learning Tools and Techniques"*. Burlington, U.S.A.: Morgan Kaufmann.

Friel, S. N., Bright, G. W., Frierson, D., & Kader, G. D. (1997). Chapter 5 A Framework for Assessing Knowledge and Learning in Statistics (K-8). In I. Gal & J. B. Garfield (Eds.), *The Assessment Challenge in Statistics Education* (pp. 55-63): IOS Press, 1997 (on behalf of the ISI).

Frontier Labs. (2018). Bioacoustic Audio Recorder. Retrieved July 6, 2018, from http://www.frontierlabs.com.au/index.php?p=1_8_Bioacoustic%E2%80%90Audio%E2%80%90Recorders

Fuller, S., Axel, A. C., Tucker, D., & Gage, S. H. (2015). Connecting soundscape to landscape: Which acoustic index best describes landscape configuration? *Ecological Indicators, 58*, 207-215. doi: 10.1016/j.ecolind.2015.05.057

Gabor, D. (1947). Theory of Communication. *Journal of the Institution of Electrical Engineers - Part I: General, 94*(73), 58. doi: 10.1049/ji-1.1947.0015

Gabora, L., Rosch, E., & Aerts, D. (2008). Toward an Ecological Theory of Concepts. *Ecological Psychology, 20*(1), 84–116. doi: 10.1080/10407410701766676

Gage, S. H., & Axel, A. C. (2014). Visualization of temporal change in soundscape power of a Michigan lake habitat over a 4-year period. *Ecological Informatics, 21*, 100–109. doi: 10.1016/j.ecoinf.2013.11.004

Gage, S. H., Towsey, M., & Kasten, E. P. (2017a). Chapter 16: Analytical Methods in Ecoacoustics. In A. Farina & S. H. Gage (Eds.), Ecoacoustics: The Ecological Role of Sounds (pp. 273-296). New Jersey, U.S.A.: John Wiley & Sons, Inc.

Gage, S. H., Wimmer, J., Tarrant, T., & Grace, P. R. (2017b). Acoustic patterns at the Samford Ecological Research Facility in South East Queensland, Australia: The Peri-Urban SuperSite of the Terrestrial Ecosystem Research Network. *Ecological Informatics, 38*, 62-75. doi: 10.1016/j.ecoinf.2017.01.002

Ganchev, T. (2017). Chapter 8 Application Examples Computational Bioacoustics (pp. 161-188). doi: 10.1515/9781614516316-008

Ganchev, T., Potamitis, I., & Fakotakis, N. (2007). *Acoustic Monitoring Of Singing Insects*. Paper presented at the 2007 IEEE International Conference on Acoustics, Speech and Signal Processing, Honolulu, U.S.A. doi:10.1109/icassp.2007.367014.

Gasc, A., Anso, J., Sueur, J., Jourdan, H., & Desutter-Grandcolas, L. (2017). Cricket Calling Communities as an Indicator of the Invasive Ant Wasmannia auropunctata in an Insular Biodiversity Hotspot. *Biological Invasions, 20*(5), 1099–1111. doi: 10.1007/s10530-017-1612-0

Gasc, A., Pavoine, S., Lellouch, L., Grandcolas, P., & Sueur, J. (2015). Acoustic indices for biodiversity assessments: Analyses of bias based on simulated bird assemblages and recommendations for field surveys. *Biological Conservation, 191*, 306-312. doi: 10.1016/j.biocon.2015.06.018

Gasc, A., Sueur, J., Jiguet, F., Devictor, V., Grandcolas, P., Burrow, C., . . . Pavoine, S. (2013a). Assessing biodiversity with sound: Do acoustic diversity indices reflect phylogenetic and functional diversities of bird communities? *Ecological Indicators, 25*, 279–287. doi: 10.1016/j.ecolind.2012.10.009

Gasc, A., Sueur, J., Pavoine, S., Pellens, R., & Grandcolas, P. (2013b). Biodiversity Sampling Using a Global Acoustic Approach: Contrasting Sites with Microendemics in New Caledonia. *Plos One, 8*(5), e65311. doi: 10.1371/journal.pone.0065311

Gerhardt, H. C. (1994). The Evolution of Vocalization in Frogs and Toads. *Annual Review of Ecology and Systematics, 25*(1), 293-324. doi: 10.1146/annurev.es.25.110194.001453

Gerhardt, H. C., & Schwartz, J. J. (1994). Chapter 5 Interspecific Interactions in Anuran Courtship. In H. Heatwole & B. K. Sullivan (Eds.), *Amphibian Biology* (Vol. 2: Social Communication, pp. 603-632). Sydney, Australia: Surrey Beatley and Sons.

Gibbs, A. J., & McIntyre, G. A. (1970). The Diagram, a Method for Comparing Sequences. Its Use with Amino Acid and Nucleotide Sequences. *European Journal of Biochemistry, 16*(1), 1–11. doi: 10.1111/j.1432-1033.1970.tb01046.x

Goller, F., & Riede, T. (2013). Integrative physiology of fundamental frequency control in birds. *Journal of Physiology - Paris, 107*(3), 230–242. doi: 10.1016/j.jphysparis.2012.11.001

Grant, R. A., Chadwick, E. A., & Halliday, T. (2009). The lunar cycle: a cue for amphibian reproductive phenology? *Animal Behaviour, 78*(2), 349–357. doi: 10.1016/j.anbehav.2009.05.007

Gray, R. M. (1984). Vector Quantization. *IEEE ASSP Magazine, 1*(2), 4-29. doi: 10.1109/massp.1984.1162229

Gregory, R. D., & van Strien, A. (2010). Wild Bird Indicators: Using Composite Population Trends of Birds as Measures of Environmental Health. *Ornithological Science, 9*(1), 3-22. doi: 10.2326/osj.9.3

Griffiths, S. R. (2013). Echolocating bats emit terminal phase buzz calls while drinking on the wing. *Behavioural Processes, 98*, 58-60. doi: 10.1016/j.beproc.2013.05.007

Grigg, G., Taylor, A., McCallum, H., & Fletcher, L. (2006). *Monitoring the impact of cane toads (Bufo marinus) on Northern Territory frogs—a progress report.* Paper presented at the Invasive animals CRC/CSIRO/Qld NRM&W Cane Toad Workshop, Brisbane, Australia. Retrieved from https://sydney.edu.au/science/biology/shine/publications/others_pubs/hagman_mattias/ProcCaneToadSymp.pdf#page=51.

Guyot, P., Eldridge, A., Eyre-Walker, Y. C., Johnston, A., Pellegrini, T., & Peck, M. (2016). *Sinusoidal modelling for ecoacoustics*. Paper presented at the Interspeech 2016 ISCA, San Francisco, U.S.A. http://sro.sussex.ac.uk/id/eprint/62317

Hall, M. I., & Ross, C. F. (2007). Eye Shape and Activity Pattern in Birds. *Journal of Zoology, 271*(4), 437–444. doi: 10.1111/j.1469-7998.2006.00227.x

Hampton, S. E., Strasser, C. A., Tewksbury, J. J., Gram, W. K., Budden, A. E., Batcheller, A. L., . . . Porter, J. H. (2013). Big data and the future of ecology. *Frontiers in Ecology and the Environment, 11*(3), 156–162. doi: 10.1890/120103

Hansen, P. (1979). Vocal learning: its role in adapting sound structures to long-distance propagation, and a hypothesis on its evolution. *Animal Behaviour, 27*, 1270-1271. doi: 10.1016/0003-3472(79)90073-3

Hartigan, J. A., & Wong, M. A. (1979). Algorithm AS 136: A K-Means Clustering Algorithm. *Applied Statistics, 28*(1), 100-108. doi: 10.2307/2346830

Healey, C. G. (1996). *Choosing effective colours for data visualization.* Paper presented at the Proceedings of Seventh Annual IEEE Visualization, San Francisco, U.S.A. Retrieved from http://vis.cs.brown.edu/docs/pdf/Healey-1996-CEC.pdf.

Healey, C. G., & Enns, J. T. (2012). Attention and Visual Memory in Visualization and Computer Graphics. *IEEE Transactions on Visualization and Computer Graphics, 18*(7), 1170-1188. doi: 10.1109/tvcg.2011.127

Henwood, K., & Fabrick, A. (1979). A Quantitative Analysis of the Dawn Chorus: Temporal Selection for Communicatory Optimization. *The American Naturalist, 114*(2), 260–274. doi: 10.1086/283473

Hill, A. P., Prince, P., Piña Covarrubias, E., Doncaster, C. P., Snaddon, J. L., & Rogers, A. (2018). AudioMoth: Evaluation of a smart open acoustic device for monitoring biodiversity and the environment. *Methods in Ecology and Evolution, 9*(5), 1199–1211. doi: 10.1111/2041-210x.12955

Hinkle, D. E., Wiersma, W., & Jurs, S. G. (2003). Chapter 5 Correlation: A Measure of Relationship *Applied Statistics for the Behavioral Sciences* (pp. 95-120). New York: Houghton Mifflin Company.

Hotelling, H. (1933). Analysis of a Complex of Statistical Variables into Principal Components. *Journal of Educational Psychology, 24*(7), 498-520. doi: 10.1037/h0070888

Hyvärinen, A., & Oja, E. (2000). Independent component analysis: algorithms and applications. *Neural Networks, 13*(4-5), 411-430. doi: 10.1016/s0893-6080(00)00026-5

Jacquet, J.-M., & Launay, F. (1997). Diurnal behavioural patterns in the houbara bustard (Chlamydotis undulata) in captivity: effects of temperature and daylength. *Applied Animal Behaviour Science, 55*(1-2), 137-151. doi: 10.1016/s0168-1591(96)01190-2

Jahn, O., Ganchev, T. D., Marques, M. I., & Schuchmann, K.-L. (2017). Automated Sound Recognition Provides Insights into the Behavioral Ecology of a Tropical Bird. *Plos One, 12*(1), e0169041. doi: 10.1371/journal.pone.0169041

Jeliazkov, A., Bas, Y., Kerbiriou, C., Julien, J.-F., Penone, C., & Le Viol, I. (2016). Large-scale semi-automated acoustic monitoring allows to detect temporal decline of bush-crickets. *Global Ecology and Conservation, 6*, 208–218. doi: 10.1016/j.gecco.2016.02.008

Jhanwar, D., Sharma, K. K., & Modani, S. G. (2015). Discrimination of Environmental Background Noise in Presence of Speech Using Sample Pairs Statistics Based Features. *Acoustical Physics, 61*(5), 585-596. doi: 10.1134/s1063771015050103

Jinnai, M., Boucher, N. J., Robertson, J., & Kleindorfer, S. (2010). *Design considerations in an automatic classification system for bird vocalisations using the Two-dimensional Geometric Distance and cluster analysis*. Paper presented at the 20th International Congress on Acoustics, ICA 2010, Sydney, Australia. Retrieved from https://www.acoustics.asn.au/conference_proceedings/ICA2010/cdrom-ICA2010/papers/p130.pdf.

Joo, W., Gage, S. H., & Kasten, E. P. (2011). Analysis and interpretation of variability in soundscapes along an urban–rural gradient. *Landscape and Urban Planning, 103*(3-4), 259– 276. doi: 10.1016/j.landurbplan.2011.08.001

Jordan, C. F. (1975). What is Ecology? *Bulletin of the Ecological Society of America, 56*(2), 2-3. doi: http://www.jstor.org.ezp01.library.qut.edu.au/stable/20166028

Josephson, R. K., & Young, D. (1979). Body Temperature and Singing in the Bladder Cicada, Cystosoma saundersii. *Journal of Experimental Biology, 80*(1), 69-81. Retrieved from http://jeb.biologists.org/content/jexbio/80/61/69.full.pdf.

Kacelnik, A., & Krebs, J. R. (1982). The Dawn Chorus in the Great Tit (Parus major): Proximate and Ultimate Causes. *Behaviour, 83*(3/4), 287-309. doi: 10.1163/156853983x00200

Kaewtip, K., Tan, L. N., Alwan, A., & Taylor, C. E. (2013). *A Robust Automatic Bird Phrase Classifier Using Dynamic Time-Warping With Prominent Region Identification*. Paper presented at the 2013 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Vancouver, Canada. doi:10.1109/icassp.2013.6637752.

Kasten, E. P., Gage, S. H., Fox, J., & Joo, W. (2012). The remote environmental assessment laboratory’s acoustic library: an archive for studying soundscape ecology. *Ecological Informatics, 12*, 50-67. doi: 10.1016/j.ecoinf.2012.08.001

Kasten, E. P., McKinley, P. K., & Gage, S. H. (2010). Ensemble extraction for classification and detection of bird species. Ecological Informatics. *Ecological Informatics, 5*(3), 153–166. doi: 10.1016/j.ecoinf.2010.02.003

Kaufman, L., & Rousseeuw, P. J. (1990). Chapter 5 Agglomerative Nesting (Program AGNES) *Finding Groups in Data: An Introduction to Cluster Analysis* (pp. 199–252). New York, U.S.A.: Wiley.

Keast, A. (1994). The Dawn Chorus in a Eucalypt Forest Bird Community, Seasonal Shifts in Timing and Contribution of Individual Species. *Corella, 18*(5), 133-140. Retrieved from http://www.absa.asn.au/publication-category/volume-118/.

Kershenbaum, A., Blumstein, B. T., Roch, M. A., Akçay, C., Backus, G., Bee, M. A., . . . Zamora-Gutierrez, V. (2016). Acoustic sequences in non-human animals: a tutorial review and prospectus. *Biological Reviews, 91*(1), 13-52. doi: 10.1111/brv.12160

Kettunen, J., Tukiainen, T., Sarin, A. P., Ortega-Alonso, A., Tikkanen, E., Lyytikäinen, L. P., . . . Ripatti, S. (2012). Genome-wide association study identifies multiple loci influencing human serum metabolite levels. *Nature Genetics, 44*(3), 269-276. doi: 10.1038/ng.1073

Key, K. H. L. (1970). Chapter 21 Orthoptera (Grasshoppers, locusts, crickets). In D. F. Waterhouse (Ed.), *The insects of Australia, A Textbook for Students and Research Workers* (pp. 323-347). Calton, Australia: Melbourne University Press.

Kholghi, M., Phillips, Y. F., Towsey, M., Sitbon, L., & Roe, P. (2018). Active Learning for Classifying Long Duration Audio Recordings of the Environment. *Methods in Ecology and Evolution, 00*, 1-11. doi: 10.1111/2041-210X.13042

Kogan, J. A., & Margoliash, D. (1998). Automated recognition of bird song elements from continuous recordings using dynamic time warping and hidden markov models: A comparative study. *Journal of the Acoustical Society of America, 103*(4), 2185-2196. doi: 10.1121/1.421364

Krause, B. L. (1992). The Habitat Niche Hypothesis: A Hidden Symphony of Animal Sounds. *The Literary review, 36*(1), 40-45. Retrieved from http://search.proquest.com/docview/222075969?accountid=222013380.

Krause, B. L. (1993). The niche hypothesis. *Soundscape Newsletter, 6*, 6-10.

Kwok, A., & Emery, N. (2016). From Where the Cicada Calls. *Wildlife Australia, 53*(2), 27-29. Retrieved from https://search.informit.com.au/.

Ladroue, C. (2012). Polar histogram pretty and useful _ Christophe Ladroue from chrisladroue.com/wp-content/uploads/2012/02/polarHistogram.R.zip

Laiolo, P., Vögeli, M., Serrano, D., & Tella, J. L. (2008). Song Diversity Predicts the Viability of Fragmented Bird Populations. *Plos One, 3*(3), e1822. doi: 10.1371/journal.pone.0001822

Lamel, L. F., Rabiner, L. R., Rosenberg, A. E., & Wilpon, J. G. (1981). An improved endpoint detector for isolated word recognition. *IEEE Transactions on Acoustics, Speech, and Signal Processing, 29*(4), 777-785. doi: 10.1109/tassp.1981.1163642

Lamirel, J.-C. (2016). *Reliable Clustering Quality Estimation from Low to High Dimensional Data*. Paper presented at the 11th Workshop on Self-Organizing Maps (WSOM 2016), Rice University, Houston, U.S.A. doi:10.1007/978-3-319-28518-4_8.

Lance, G. N., & Williams, W. T. (1967). A General Theory of Classificatory Sorting Strategies: 1. Hierarchical Systems. *The Computer Journal, 9*(4), 373–380. doi: 10.1093/comjnl/9.4.373

Larsen, F. W., Bladt, J., Balmford, A., & Rahbek, C. (2012). Birds as biodiversity surrogates: will supplementing birds with other taxa improve effectiveness? *Journal of Applied Ecology, 49*(2), 349-356. doi: 10.1111/j.1365-2664.2011.02094.x

Leach, E. C. (2016). Notes on the Zoothera thrushes in the Tweed Range of north-eastern New South Wales. *Australian Field Ornithology, 33*, 240-243. doi: 10.20938/afo33240243

Lehmann, G. U. C., Frommolt, K.-H., Lehmann, A. W., & Riede, K. (2014). Baseline data for automated acoustic monitoring of Orthoptera in a Mediterranean landscape, the Hymettos, Greece. *Journal of Insect Conservation, 18*(5), 909-925. doi: 10.1007/s10841-014-9700-2

Lellouch, L., Pavoine, S., Jiguet, F., Glotin, H., & Sueur, J. (2014). Monitoring temporal change of bird communities with dissimilarity acoustic indices. *Methods in Ecology and Evolution, 5*(6), 495-505. doi: 10.1111/2041-210x.12178

Lemon, J. (2006). Plotrix: a package in the red light district of R. *R-News, 6*(4), 8-12.

Leroy, E. C., Samaran, F., Bonnel, J., & Royer, J.-Y. (2016). Seasonal and Diel Vocalization Patterns of Antarctic Blue Whale (Balaenoptera musculus intermedia) in the Southern Indian Ocean: A Multi-Year and Multi-Site Study. *Plos One, 11*(11), e0163587. doi: 10.1371/journal.pone.0163587

Lewis, T., & Taylor, L. R. (1965). Diurnal periodicity of flight by insects. *Transactions of the Royal Entomological Society of London, 116*(15), 393–435. doi: 10.1111/j.1365-2311.1965.tb02304.x

Lin, J., Keogh, E., Lonardi, S., & Chiu, B. (2003). *A symbolic representation of time series with implications for streaming algorithms*. Paper presented at the 8th ACM SIGMOD Workshop on Research Issues in Data Mining and Knowledge Discovery, San Diego, U.S.A. http://static.cs.brown.edu/courses/csci2270/papers/representation.pdf

Lunilettronik. (2016). International Institute of Ecoacoustics - Soundscape Explorer Terrestrial (SET). from http://lunilettronik.it/soundscape_explorer/

Lynch, E., Joyce, D., & Fristrup, K. (2011). An assessment of noise audibility and sound levels in U.S. National Parks. *Landscape Ecology, 26*(9), 1297–1309. doi: 10.1007/s10980-011-9643-x

Malavasi, R., & Farina, A. (2013). Neighbours' talk: interspecific choruses among songbirds. *Bioacoustics, 22*(1), 33–48. doi: 10.1080/09524622.2012.710395

Mammides, C., Goodale, E., Dayananda, S. K., Kang, L., & Chen, J. (2017). Do acoustic indices correlate with bird diversity? Insights from two biodiverse regions in Yunnan Province, south China. *Ecological Indicators, 82*, 470-477. doi: 10.1016/j.ecolind.2017.07.017

Matthews, L. P., McCordic, J. A., & Parks, S. E. (2014). Remote Acoustic Monitoring of North Atlantic Right Whales (Eubalaena glacialis) Reveals Seasonal and Diel Variations in Acoustic Behavior. *Plos One, 9*(3), e91367. doi: 10.1371/journal.pone.0091367

Mazaris, A. D., Kallimanis, A. S., Chatzigianidis, G., Papadimitriou, K., & Pantis, J. D. (2009). Spatiotemporal analysis of an acoustic environment: interactions between landscape features and sounds. *Landscape Ecology, 24*(6), 817–831. doi: 10.1007/s10980-009-9360-x

McAlpine, C. A., Peterson, A., & Norman, P. (2005). The South East Queensland Forests Agreement: lessons for biodiversity conservation. *Pacific Conservation Biology, 11*(1), 3-13. doi: 10.1071/PC050003

McQuillan, P. B., Watson, J. E. M., Obendorf, D., Fitzgerald, N. B., & Leaman, D. (2009). The importance of ecological processes for terrestrial biodiversity conservation in Tasmania – a review. *Pacific Conservation Biology, 15*(3), 171–196. doi: 10.1071/pc090171

Meek, P. D., Ballard, G., Claridge, A., Kays, R., Moseby, K., O'Brien, T., . . . Townsend, S. (2014). Recommended guiding principles for reporting on camera trapping research. *Biodiversity and Conservation, 23*(9), 2321–2343. doi: 10.1007/s10531-014-0712-8

Mennill, D. J., & Rogers, A. C. (2006). Whip It Good! Geographic Consistency in Male Songs and Variability in Female Songs of the Duetting Eastern Whipbird Psophodes olivaceus. *Journal of Avian Biology, 37*(1), 93-100. doi: 10.1111/j.0908-8857.2006.03548.x

Mennis, J. L., Peuquet, D. J., & Qian, L. (2000). A conceptual framework for incorporating cognitive principles into geographical database representation. *International Journal of Geographical Information Science, 14*(6), 501–520. doi: 10.1080/136588100415710

Mesentean, S., Fischer, S., & Smith, J. C. (2006). Analyzing Large-Scale Structural Change in Proteins: Comparison of Principal Component Projection and Sammon Mapping. *Proteins: Structure, Function, and Bioinformatics, 64*(1), 210–218. doi: 10.1002/prot.20981

Morfi, V., & Stowell, D. (2017). *Deductive refinement of species labelling in weakly labelled birdsong recordings.* Paper presented at the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), New Orleans, U.S.A. doi:10.1109/icassp.2017.7952237.

Mortimer, J. A. J., & Greene, T. C. (2017). Investigating bird call identification uncertainty using data from processed audio recordings. *New Zealand Journal of Ecology, 41*(1), 126-133. doi: 10.20417/nzjecol.41.10

Morton, E. S. (1975). Ecological Sources of Selection on Avian Sounds. *The American Naturalist, 109*(965), 17-34. doi: 10.1086/282971

Mullet, T. C. (2017). Chapter 12: Connecting Soundscapes to Landscapes: Modeling the Spatial Distribution of Sound. In A. Farina & S. H. Gage (Eds.), *Ecoacoustics: The Ecological Role of Sounds* (pp. 211-223). New Jersey, U.S.A.: John Wiley & Sons, Inc.

Mullet, T. C., Farina, A., & Gage, S. H. (2017a). The Acoustic Habitat Hypothesis: An Ecoacoustics Perspective on Species Habitat Selection. *Biosemiotics, 10*(3), 319–336. doi: 10.1007/s12304-017-9288-5

Mullet, T. C., Gage, S. H., Morton, J. M., & Huettmann, F. (2016). Temporal and spatial variation of a winter soundscape in south-central Alaska. *Landscape Ecology, 31*(5), 1117–1137. doi: 10.1007/s10980-015-0323-0

Mullet, T. C., Morton, J. M., Gage, S. H., & Huettmann, F. (2017b). Acoustic Footprint of Snowmobile Noise and Natural Quiet Refugia in an Alaskan Wilderness. *Natural Areas Journal, 37*(3), 332-349. doi: 10.3375/043.037.0308

Müllner, D. (2013). fastcluster: Fast Hierarchical, Agglomerative Clustering Routines for R and Python. *Journal of Statistical Software, 53*(9), 1-18. doi: 10.18637/jss.v053.i09

Murtagh, F., & Legendre, P. (2014). Ward's Hierarchical Agglomerative Clustering Method: Which Algorithms Implement Ward's Criterion? *Journal of Classification, 31*(3), 274-295. doi: 10.1007/s00357-014-9161-z

Myatt, G. J., & Johnson, W. P. (2011). Chapter 2 The Cognitive and Visual Systems *Making Sense of Data III: A Practical Guide to Designing Interactive Data Visualizations* (pp. 20-64). Hoboken, U.S.A.: John Wiley & Sons, Inc. doi:10.1002/9781118121610.ch2.

Naguib, M., & Wiley, R. H. (2001). Estimating the distance to a source of sound: mechanisms and adaptations for long-range communication. *Animal Behaviour, 62*(5), 825–837. doi: 10.1006/anbe.2001.1860

Nakazawa, M. (2015). 'fmsb' (R package) Version 0.5.2. Retrieved from https://cran.r-project.org/web/packages/fmsb/fmsb.pdf.

Napoletano, B. M. (2004). *Measurement, quantification and interpretation of acoustic signals within an ecological context.* (Masters of Science), Michigan State University. Retrieved from https://www.researchgate.net/profile/Brian_Napoletano2/publication/34000324

Napoletano, B. M. (2017). Chapter 10: Integrating Biophony into Biodiversity Measurement and Assessment. In A. Farina & S. H. Gage (Eds.), Ecoacoustics: The Ecological Role of Sounds (pp. 169-192). New Jersey, U.S.A.: John Wiley & Sons, Inc.

Navon, S., Mizrach, A., Hetzroni, A., & Ungar, E. D. (2013). Automatic recognition of jaw movements in free-ranging cattle, goats and sheep, using acoustic monitoring. *Biosystems Engineering, 114*(4), 474-483. doi: 10.1016/j.biosystemseng.2012.08.005

Nguyen, T.-D., & Kwoh, C.-K. (2015, November 1-4). *Efficient agglomerative hierarchical clustering for biological sequence analysis.* Paper presented at the TENCON 2015 - 2015 IEEE Region 10 Conference, Macau, China. doi:10.1109/TENCON.2015.7373194.

Novak, S. J. (2007). The role of evolution in the invasion process. *Proceedings of the National Academy of Sciences, 104*(10), 3671–3672. doi: 10.1073/pnas.0700224104

Obrist, M. K., Pavan, G., Sueur, J., Riede, K., Llusia, D., & Márquez, R. (2010). Chapter 5 Bioacoustics approaches in biodiversity inventories. In J. Eymann, J. Degreef, C. Häuser, J. C. Monje, Y. Samyn, & D. VandenSpiegel (Eds.), *Manual on Field Recording Techniques and Protocols for All Taxa Biodiverity Inventorie* (pp. 68-99. Retrieved from https://www.dora.lib64ri.ch/wsl/islandora/object/wsl:11922).

Oseen, K. L., & Wassersug, R. J. (2002). Environmental factors influencing calling in sympatric anurans. *Oecologia, 133*(4), 616–625. doi: 10.1007/s00442-002-1067-5

Otte, D., & Cade, W. (1983). *African Crickets (Gryllidae). 1. Teleogryllus of Eastern and Southern Africa*. Paper presented at the Proceedings of the Academy of Natural Sciences of Philadelphia. http://www.jstor.org/stable/4064798

Pearson, K. (1901). On lines and planes of closest fit to systems of points in space. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science, 2*(11), 559-572.

Peck, M. R., Maddock, S. T., Morales, J. N., Oñate, H., Mafla-Endara, P., Peñafiel, V. A., . . . Tolhurst, B. A. (2014). Cost-Effectiveness of Using Small Vertebrates as Indicators of Disturbance. *Conservation Biology, 28*(5), 1331–1341. doi: 10.1111/cobi.12373

Pekin, B. K., Jung, J., Villanueva-Rivera, L. J., Pijanowski, B. C., & Ahumada, J. A. (2012). Modeling acoustic diversity using soundscape recordings and LIDAR-derived metrics of vertical forest structure in a neotropical rainforest. *Landscape Ecology, 27*(10), 1513-1522. doi: 10.1007/s10980-012-9806-4

Phillips, Y. F., Towsey, M., & Roe, P. (2017, 7-10 November). *Visualization of Environmental Audio using Ribbon Plots and Acoustic State Sequences.* Paper presented at the IEEE International Symposium on Big Data Visual Analytics (BDVA), Adelaide, Australia. doi:10.1109/bdva.2017.8114628.

Phillips, Y. F., Towsey, M., & Roe, P. (2018). Revealing the Ecological Content of Long-duration Audio-recordings of the Environment through Clustering and Visualisation. *Plos One, 13*(3), e0193345. doi: 10.1371/journal.pone.0193345

Pieretti, N., Duarte, M. H. L., Sousa-Lima, R. S., Rodrigues, M., Young, R. J., & Farina, A. (2015). Determining Temporal Sampling Schemes for Passive Acoustic Studies in Different Tropical Ecosystems. *Tropical Conservation Science, 8*(1), 215–234. doi: 10.1177/194008291500800117

Pieretti, N., Farina, A., & Morri, D. (2011). A new methodology to infer the singing activity of an avian community: the acoustic complexity index (ACI). *Ecological Indicators, 11*(3), 868–873. doi: 10.1016/j.ecolind.2010.11.005

Pijanowski, B. C., Farina, A., Gage, S. H., Dumyahn, S. L., & Krause, B. L. (2011a). What is soundscape ecology? An introduction and overview of an emerging new science. *Landscape Ecology, 26*(9), 1213-1232. doi: 10.1007/s10980-011-9600-8

Pijanowski, B. C., Villanueva-Rivera, L. J., Dumyahn, S. L., Farina, A., Krause, B. L., Napoletano, B. M., . . . Pieretti, N. (2011b). Soundscape Ecology: The Science of Sound in the Landscape. *BioScience, 61*(3), 203-216. doi: 10.1525/bio.2011.61.3.6

Pizzey, G. (2014). *The Field Guide to the Birds of Australia* (S. Pizzey Ed.): Harper Collins Publishers Australia Pty Limited, Sydney, Australia.

Popple, L. W. (2006). The Cicadas of Central Eastern Australia. Retrieved 10 December 2015, 2015, from http://sci-s03.bacs.uq.edu.au/ins-info/index.htm

Potamitis, I. (2014). Automatic Classification of a Taxon-Rich Community Recorded in the Wild. *Plos One, 9*(5), e96936. doi: 10.1371/journal.pone.0096936

Potter, R. K. (1945). Visible patterns of sound. *Science, 102*(2654), 463–470. doi: 10.1126/science.102.2654.463

Priyadarshani, N., Marsland, S., & Castro, I. (2018). Automated birdsong recognition in complex acoustic environments: A review. *Journal of Avian Biology, 49*(5), jav–01447. doi: 10.1111/jav.01447

Qi, J., Gage, S. H., Joo, W., Napoletano, B., & Biswas, S. (2007). Chapter 17 Soundscape Characteristics of an Environment: A New Ecological Indicator of Ecosystem Health. In W. Ji (Ed.), *Wetland and Water Resource Modeling and Assessment : A Watershed Perspective* (pp. 201-211). Boca Raton, U.S.A.: CRC Press.

Queensland Government. (2013a). Gympie National Park Management Statement. Retrieved 30 December 2012, from http://www.npsr.qld.gov.au/managing/plans-strategies/statements/pdf/gympie.pdf

Queensland Government. (2013b). Woondum National Park Management Statement. from http://www.npsr.qld.gov.au/managing/plans-strategies/statements/pdf/woondum.pdf

Queensland Government. (2015a). Request a species list. Retrieved 14/10/2015, from https://environment.ehp.qld.gov.au/report-request/species-list/

Queensland Government. (2015b). Wildlife of Woondum National Park, Wetland Information. Retrieved 30 December 2015, from http://wetlandinfo.ehp.qld.gov.au/wetlands/facts-maps/wildlife/?AreaID=national-park-woondum

Queensland Government. (2015c). Wildlife Online Extract (Gympie National Park). Retrieved 14 October 2015, from https://environment.ehp.qld.gov.au/report-request/species-list/

Queensland Herbarium. (2014). Regional Ecosystem map request. Retrieved 21 August 2014, from https://environment.ehp.qld.gov.au/map-request/re-broad-veg-group/

Queensland Herbarium. (2015). Regional Ecosystem Description Database (REDD). Version 9.0 (April 2015). (DSITI: Brisbane). Retrieved 8 February 2016, from https://www.qld.gov.au/environment/plants-animals/plants/ecosystems/download/

Queensland Museum. (2003). Dry Eucalypt forest. In M. Ryan (Ed.), *Wild Plants of Greater Brisbane: a Queensland Museum guide* (pp. 93-198). Brisbane, Australia: Queensland Museum.

Quinlan, J. R. (1992). *C4.5 : Programs for Machine Learning*. ProQuest Ebook Central: Elsevier Science & Technology. Retrieved from https://ebookcentral.proquest.com/lib/qut/detail.action?docID=1876696.

R Core Team. (2016). R: A Language and Environment for Statistical Computing. Vienna, Austria Retrieved from http://www.R-project.org/

Rabiner, L. R. (1989). *A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition*. Paper presented at the IEEE, AT&T Bell Lab., Murray Hill, New Jersey, U.S.A.

Rankin, L., & Axel, A. C. (2017). Chapter 8 Biodiversity Assessment in Tropical Biomes using Ecoacoustics: Linking Soundscape to Forest Structure in a Human-dominated Tropical Dry Forest in Southern Madagascar. In A. Farina & S. H. Gage (Eds.), Ecoacoustics: The Ecological Role of Sounds (pp. 129-144). New Jersey, U.S.A.: John Wiley & Sons, Inc.

Retamosa Izaguirre, M. I., Ramírez-Alán, O., & De la O Castro, J. (2018). Acoustic indices applied to biodiversity monitoring in a Costa Rica dry tropical forest. *Journal of Ecoacoustics, 2*, TNW2NP. doi: 10.22261/jea.tnw2np

Reyes-Arriagada, R., Jiménez, J. E., & Rozzi, R. (2015). Daily patterns of activity of passerine birds in a Magellanic sub-Antarctic forest at Omora Park (55°S), Cape Horn Biosphere Reserve, Chile. *Polar Biology, 38*(3), 401–411. doi: 10.1007/s00300-014-1596-5

Richards, D. G., & Wiley, R. H. (1980). Reverberations and Amplitude Fluctuations in the Propagation of Sound in a Forest: Implications for Animal Communication. *The American Naturalist, 115*(3), 381–399. doi: 10.1086/283568

Riede, K. (1998). Acoustic monitoring of Orthoptera and its potential for conservation. *Journal of Insect Conservation, 2*(3-4), 217–223. doi: 10.1023/A:1009695813606

Rocha, L. H. S., Ferreira, L. S., Paula, B. C., Rodrigues, F. H. G., & Sousa-Lima, R. S. (2015). An evaluation of manual and automated methods for detecting sounds of maned wolves (Chrysocyon brachyurus Illiger 1815). *Bioacoustics: The International Journal of Animal Sound and its Recording, 24*(2), 185–198. doi: 10.1080/09524622.2015.1019361

Rocha, L. H. S., Ferreira, L. S., Venticinque, E. M., Rodrigues, F. H. G., & Sousa-Lima, R. S. (2017). Temporal and environmental influences on long-distance calling by free-ranging maned wolves (Chrysocyon brachyurus). *Journal of Mammalogy, 98*(1), gyw171. doi: 10.1093/jmammal/gyw171

Rodriguez, A., Gasc, A., Pavoine, S., Grandcolas, P., Gaucher, P., & Sueur, J. (2014). Temporal and spatial variability of animal sound within a neotropical forest. *Ecological Informatics, 21*, 133-143. doi: 10.1016/j.ecoinf.2013.12.006

Rosemartin, A. H., Crimmins, T. M., Enquist, C. A. F., Gerst, K. L., Kellermann, J. L., Posthumus, E. E., . . . Weltzin, J. F. (2014). Organizing phenological data resources to inform natural resource conservation. *Biological Conservation, 173*, 90–97. doi: 10.1016/j.biocon.2013.07.003

Ross, S. R. P.-J., Friedman, N. R., Dudley, K. L., Yoshimura, M., Yoshida, T., & Economo, E. P. (2018). Listening to ecosystems: data-rich acoustic monitoring through landscape-scale sensor networks. *Ecological Research, 33*(1), 135-147. doi: 10.1007/s11284-017-1509-5

Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics, 20*, 53–65. doi: 10.1016/0377-0427(87)90125-7

Roy, D., & Elepfandt, A. (1993). Bioacoustic analysis of frog calls from northeast India. *Journal of Biosciences, 18*(3), 381-393. doi: 10.1007/bf02702996

Rychtáriková, M., & Vermeir, G. (2013). Soundscape categorization on the basis of objective acoustical parameters. *Applied Acoustics, 74*(2), 240–247. doi: 10.1016/j.apacoust.2011.01.004

Saito, T., Miyamura, H. N., Yamamoto, M., Saito, H., Hoshiya, Y., & Kaseda, T. (2005). *Two-tone pseudo coloring: compact visualization for one-dimensional data.* Paper presented at the IEEE Symposium on Information Visualization, Minneapolis, U.S.A. doi:10.1109/infvis.2005.1532144.

Saitta, S., Raphael, B., & Smith, I. F. C. (2007). A Bounded Index for Cluster Validity - Lecture Notes in Computer Science *Machine Learning and Data Mining in Pattern Recognition* (pp. 174-187). Berlin, Germany: Springer.

Sammon, J. W. (1969). *A Nonlinear Mapping for Data Structure Analysis*. Paper presented at the IEEE Transactions on Computers, 10.1109/t-c.1969.222678.

Sanborn, A. F., & Maté, S. (2000). Thermoregulation and the effect of body temperature on call temporal parameters in the cicada Diceroprocta olympusa (Homoptera: Cicadidae). *Comparative Biochemistry and Physiology Part A: Molecular & Integrative Physiology, 125*(1), 141–148. doi: 10.1016/s1095-6433(99)00169-5

Sanborn, A. F., Villet, M. H., & Phillips, P. K. (2003). Hot-blooded singers: endothermy facilitates crepuscular signaling in African platypleurine cicadas (Hemiptera: Cicadidae: Platypleura spp.). *Naturwissenschaften, 90*(7), 305-308. doi: 10.1007/s00114-003-0428-1

Sankupellay, M., Towsey, M., Truskinger, A., & Roe, P. (2015). *Visual fingerprints of the acoustic environment. The use of acoustic indices to characterise natural habitats*. Paper presented at the IEEE International Symposium on Big Data Visual Analytics (BDVA), Hobart, Australia. doi:10.1109/bdva.2015.7314306.

Schafer, R. M. (1994). *The soundscape: Our sonic environment and the tuning of the world*. Rochester, U.S.A.: Destiny Books.

Schafer, R. W., & Rabiner, L. R. (1973). *Design and simulation of a speech analysis-synthesis system based on short-time Fourier analysis*. Paper presented at the IEEE Transactions on Audio and Electroacoustics. doi: 10.1109/tau.1973.1162474.

Sekercioglu, C. H. (2011). Functional Extinctions of Bird Pollinators Cause Plant Declines. *Science, 331*(6020), 1019-1020. doi: 10.1126/science.1202389

Shneiderman, B. (1996). *The Eyes Have It: A Task by Data Type Taxonomy for Information Visualizations.* Paper presented at the IEEE Symposium on Visual Languages, Boulder, U.S.A. doi:10.1016/b978-155860915-0/50046-9.

Slabbekoorn, H., & Ripmeester, E. A. P. (2008). Birdsong and anthropogenic noise: implications and applications for conservation. *Molecular Ecology, 17*(1), 72-83. doi: 10.1111/j.1365-294x.2007.03487.x

Staicer, C. A., Spector, D. A., & Horn, A. G. (1996). Chapter 24 The dawn chorus and other diel patterns in acoustic signaling. In D. E. Kroodsma & E. H. Miller (Eds.), *Ecology and Evolution of Acoustic Communication in Birds* (pp. 426–453). Ithaca, U.S.A.: Cornell University Press.

Stehelin, T. E., & Lein, M. R. (2014). Social stimulation of dawn singing in Dusky Flycatchers: a serendipitous experiment. *Journal of Field Ornithology, 85*(1), 63-74. doi: 10.1111/jofo.12050

Steinbauer, M. J., Haslem, A., & Edwards, E. D. (2012). Using meteorological and lunar information to explain catch variability of Orthoptera and Lepidoptera from 250 W Farrow light traps. *Insect Conservation and Diversity, 5*(5), 367–380. doi: 10.1111/j.1752-4598.2011.00170.x

Sueur, J. (2014). Seewave: A very short introduction to sound analysis for those who like elephant trumpet calls or other wildlife sound. Retrieved 16 January 2015, from http://cran.r-project.org/web/packages/seewave/vignettes/seewave_analysis.pdf

Sueur, J. (2018a). Chapter 11 Spectrographic Visualization. In R. Gentleman, K. Hornik, & G. Parmigiani (Eds.), *Sound Analysis and Synthesis with R* (pp. 309-379). Cham, Switzerland: Springer International Publishing AG part of Springer Nature.

Sueur, J. (2018b). Chapter 16 Indices for Ecoacoustics. In R. Gentleman, K. Hornik, & G. Parmigiani (Eds.), *Sound Analysis and Synthesis with R* (pp. 479-519). Cham, Switzerland: Springer International Publishing AG part of Springer Nature.

Sueur, J., & Farina, A. (2015). Ecoacoustics: the Ecological Investigation and Interpretation of Environmental Sound. *Biosemiotics, 8*(3), 493-502. doi: 10.1007/s12304-015-9248-x

Sueur, J., Farina, A., Gasc, A., Pieretti, N., & Pavoine, S. (2014). Acoustic Indices for Biodiversity Assessment and Landscape Investigation. *Acta Acustica United With Acustica, 100*(4), 772–781. doi: 10.3813/AAA.918757

Sueur, J., Gasc, A., Grandcolas, P., & Pavoine, S. (2012). Chapter 1 (Section II) Global estimation of animal diversity using automatic acoustic sensors. In J.-F. Le Galliard, J.-M. Guarini, & F. Gaill (Eds.), *Sensors for ecology* (pp. 99-117). Paris, : CNRS.

Sueur, J., Pavoine, S., Hamerlynck, O., & Duvail, S. (2008). Rapid Acoustic Survey for Biodiversity Appraisal. *Plos One, 3*(12), e4065. doi: 10.1371/journal.pone.0004065

Taboada-Crispi, A., Sahli, H., Orozco-Monteagudo, M., Hernández-Pacheco, D., & Falcón-Ruiz, A. (2009). Chapter 27 Anomaly Detection in Medical Image Analysis. In T. Exarchos, A. Papadopoulos, & D. Fotiadis (Eds.), *Handbook of Research on Advanced Techniques in Diagnostic Imaging and Biomedical Applications* (pp. 426-446). Hershey, U.S.A.: IGI Global.

Tachibana, R. O., Oosugi, N., & Okanoya, K. (2014). Semi-Automatic Classification of Birdsong Elements Using a Linear Support Vector Machine. *Plos One, 9*(3), e92584. doi: 10.1371/journal.pone.0092584

The LaTeX Project. (2018). LaTeX – A document preparation system. Retrieved April 3, 2018, from https://www.latex-project.org/

Thomas, R. J., Szeskely, T., Cuthill, I. C., Harper, D. G. C., Newson, S. E., Frayling, T. D., & Wallis, P. D. (2002). Eye size in birds and the timing of song at dawn. *Proceedings of the Royal Society B: Biological Sciences, 269*(1493), 831–837. doi: 10.1098/rspb.2001.1941

Thomisch, K., Boebel, O., Clark, C. W., Hagen, W., Spiesecke, S., Zitterbart, D. P., & Van Opzeeland, I. (2016). Spatio-temporal patterns in acoustic presence and distribution of Antarctic blue whales Balaenoptera musculus intermedia in the Weddell Sea. *Endangered Species Research, 30*(1), 239–253. doi: 10.3354/esr00739

Thorne, R., & Shepherd, D. (2013). Quiet as an Environmental Value: A Contrast between Two Legislative Approaches. *International Journal of Environmental Research and Public Health, 10*(7), 2741-2759. doi: 10.3390/ijerph10072741

Tobias, J. A., Aben, J., Brumfield, R. T., Derryberry, E. P., Halfwerk, W., Slabbekoorn, H., & Seddon, N. (2010). Song Divergence by Sensory Drive in Amazonian Birds. *Evolution, 64*(10), 2820-2839. doi: 10.1111/j.1558-5646.2010.01067.x

Toledo, L. F., Martins, I. A., Bruschi, D. P., Passos, M. A., Alexandre, C., & Haddad, C. F. B. (2015). The anuran calling repertoire in the light of social context. *Acta Ethologica, 18*(2), 87–99. doi: 10.1007/s10211-014-0194-4

Torija, A. J., Ruiz, D. P., & Ramos-Ridao, A. F. (2013). Application of a methodology for categorizing and differentiating urban soundscapes using acoustical descriptors and semantic-differential attributes. *The Journal of the Acoustical Society of America, 134*(1), 791-802. doi: 10.1121/1.4807804

Towsey, M. (2017). The calculation of acoustic indices derived from long-duration recordings of the natural environment. QUT ePrints, Brisbane, Australia. https://eprints.qut.edu.au/110634/. 1-11.

Towsey, M., Roelofs, A., Phillips, Y., Truskinger, A., & Roe, P. (2018a). *Content description of very-long-duration recordings of the environment*. Paper presented at the 10th International Conference on Ecological Informatics, Jena, Germany.

Towsey, M., Truskinger, A., & Roe, P. (2016). Audio Analysis Software (Version 16.06.3430.0) [Computer software]. Brisbane: QUT Ecoacoustics Research Group. Retrieved from https://github.com/QutEcoacoustics/audio-analysis/releases/tag/v16.06.3431.0 and https://github.com/QutEcoacoustics/audio-analysis.

Towsey, M., Wimmer, J., Williamson, I., & Roe, P. (2014a). The use of acoustic indices to determine avian species richness in audio-recordings of the environment. *Ecological Informatics, 21*, 210-219. doi: 10.1016/j.ecoinf.2013.11.007

Towsey, M., Zhang, L., Cottman-Fields, M., Wimmer, J., Zhang, J., & Roe, P. (2014b). Visualization of long-duration acoustic recordings of the environment. *Procedia Computer Science, 29*, 703-712. doi: 10.1016/j.procs.2014.05.063

Towsey, M., Znidersic, E., Broken-Brow, J., Indraswari, K., Watson, D. M., Phillips, Y., . . . Roe, P. (2018b). Long-duration, False-colour Spectrograms for Detecting Species in Large Audio Datasets. *Journal of Ecoacoustics, 2*, IUSWUI. doi: 10.22261/JEA.IUSWUI

Towsey, M. W., Truskinger, A. M., & Roe, P. (2015, 14-17 November 2015). *The Navigation and Visualisation of Environmental Audio using Zooming Spectrograms.* Paper presented at the IEEE International Conference on Data Mining Workshop (ICDMW), Atlantic City, U.S.A. doi:10.1109/icdmw.2015.118.

Truskinger, A., Cottman-Fields, M., Eichinski, P., Towsey, M., & Roe, P. (2014). *Practical Analysis of Big Acoustic Sensor Data for Environmental Monitoring*. Paper presented at the 2014 IEEE Fourth International Conference on Big Data and Cloud Computing, Sydney, Australia. doi:10.1109/bdcloud.2014.29.

Truskinger, A., Cottman-Fields, M., & Roe, P. (2017). Acoustic Workbench (Version 1.2.2) [Computer software]. Brisbane: QUT Ecoacoustics Research Group. from https://github.com/QutBioacoustics/

Tryjanowski, P., & Morelli, F. (2015). Presence of Cuckoo reliably indicates high bird diversity: A case study in a farmland area. *Ecological Indicators, 55*, 52-58. doi: 10.1016/j.ecolind.2015.03.012

Tucker, D., Gage, S. H., Williamson, I., & Fuller, S. (2014). Linking ecological condition and the soundscape in fragmented Australian forests. *Landscape Ecology*, *29*(4), 745–758. doi: 10.1007/s10980-014-0015-1

Tucker, D. I. (2016). *The assessment of ecological condition in south-east Queensland, Australia: An evaluation of reliability across variable environments and surrogate efficacy for biodiversity values.* (Doctor of Philosophy), Queensland University of Technology.

Turgeon, P. J., Van Wilgenburg, S. L., & Drake, K. L. (2017). Microphone variability and degradation: implications for monitoring programs employing autonomous recording units. *Avian Conservation and Ecology*, *12*(1), 9. doi: 10.5751/ACE-00958-120109

U.S. Naval Observatory (USNO). (2017). Phases of the Moon. Retrieved 24 March 2017, from http://aa.usno.navy.mil/data/docs/MoonPhase.php

Ulloa, J. S., Aubin, T., Llusia, D., Bouveyron, C., & Sueur, J. (2018). Estimating animal acoustic diversity in tropical environments using unsupervised multiresolution analysis. *Ecological Indicators, 90*, 346–355. doi: 10.1016/j.ecolind.2018.03.026

Ulloa, J. S., Gasc, A., Gaucher, P., Aubin, T., Réjou-Méchain, M., & Sueur, J. (2016). Screening large audio datasets to determine the time and space distribution of Screaming Piha birds in a tropical forest. *Ecological Informatics, 31*, 91–99. doi: 10.1016/j.ecoinf.2015.11.012

Uovision Europe. (2014). Uovision Panoramic UV572 12MP HD - English User Manual. Retrieved 5 June 2015, from http://www.uovisioneurope.com/en/content/7-user-manuals-uovision-trail-camera

van der Maaten, L., & Hinton, G. (2008). Visualizing Data using t-SNE. *Journal of Machine Learning Research, 9*, 2579-2605. Retrieved from http://www.jmlr.org/papers/volume2579/vandermaaten2508a/vandermaaten2508a.pdf.

Van Dyck, S. (1995). Chapter 27 Monotremes and Marsupials. In M. Ryan (Ed.), *Wildlife of Greater Brisbane* (pp. 281-296). Brisbane: Queensland Museum.

van Staaden, M. J., & Römer, H. (1997). Sexual signalling in bladder grasshoppers: tactical design for maximizing calling range. *Journal of Experimental Biology*, *200*(20), 2597-2608. Retrieved from http://jeb.biologists.org/content/jexbio/2200/2520/2597.full.pdf.

Van Wyk, J. W., & Ferguson, J. W. H. (1995). Communicatory constraints on field crickets Gryllus bimaculatus calling at low ambient temperatures. *Journal of Insect Physiology, 41*(10), 837–841. doi: 10.1016/0022-1910(95)00055-y

Venables, W. N., & Ripley, B. D. (2002). *Modern Applied Statistics with S*. New York: Springer.

Villanueva-Rivera, L. C., Pijanowski, B. C., Doucette, J., & Pekin, B. (2011). A primer of acoustic analysis for landscape ecologists. *Landscape Ecology, 26*(9), 1233-1246. doi: 10.1007/s10980-011-9636-9

Walker, T. J. (1962). Factors responsible for intraspecific variation in the calling songs of crickets. *Evolution*, *16*(4), 407-428. doi: 10.2307/2406176

Ward, J. H. (1963). Hierarchical Grouping to Optimize an Objective Function. *Journal of the American Statistical Association*, *58*(301), 236-244. doi: 10.2307/2282967

Welsh, H. H., & Ollivier, L. M. (1998). Stream Amphibians as Indicators of Ecosystem Stress: A Case Study from California's Redwoods. *Ecological Applications*, *8*(4), 1118–1132. doi: 10.2307/2640966

Whytock, R. C., & Christie, J. (2016). Solo: an open source, customizable and inexpensive audio recorder for bioacoustic research. *Methods in Ecology and Evolution*, *8*(3), 308-312. doi: 10.1111/2041-210x.12678

Wildlife Acoustics. (2013). Song Meter SM2+ User Guide. Retrieved December 1, 2015, from https://www.wildlifeacoustics.com/images/documentation/SM2plus1.pdf

Wildlife Acoustics. (2017). Kaleidoscope 4.3.1 Documentation. Retrieved June 21, 2017, from https://www.wildlifeacoustics.com/images/documentation/Kaleidoscope.pdf

Wiley, R. H., & Richards, D. G. (1978). Physical constraints on acoustic communication in the atmosphere: Implications for the evolution of animal vocalizations. *Behavioral Ecology and Sociobiology, 3*(1), 69–94. doi: 10.1007/bf00300047

Wiley, R. H., & Richards, D. G. (1982). Chapter 5 Adaptations for Acoustic Communication in Birds: Sound Transmission and Signal Detection. In D. E. Kroodsma & E. H. Miller (Eds.), *Acoustic Communication in Birds. Volume 1 Production, Perception and Design Features of Sounds* (pp. 131-182). London, United Kingdom: Academic Press, Inc. (London) Ltd.

Winter, J. W. (1976). *The behaviour and social organisation of the brush-tail possum (Trichosurus vulpecula: Kerr).* (Doctor of Philosophy Monograph), University of Queensland. Retrieved from https://espace.library.uq.edu.au/view/UQ:388573

Witten, I. H., Frank, E., Trigg, L., Hall, M., Holmes, G., & Cunningham, S. J. (1999). Weka: Practical machine learning tools and techniques with Java implementations. (Working paper 99/11). Hamilton, New Zealand. University of Waikato, Department of Computer Science. Retrieved from https://researchcommons.waikato.ac.nz/handle/10289/1040.

Wong, B. (2011). Color blindness. *Nature Methods, 8*(6), 441. doi: 10.1038/nmeth.1618

Wormington, K. R., Lamb, D., McCallum, H. I., & Moloney, D. J. (2002). Habitat requirements for the conservation of arboreal marsupials in Dry Sclerophyll Forests of Southeast Queensland, Australia. *Forest Science*, *48*(2), 217-227. Retrieved from https://academic.oup.com/forestscience/.

Wu, X., Kumar, V., Quinlan, J. R., Ghosh, J., Yang, Q., Motoda, H., . . . Steinberg, D. (2008). Top 10 algorithms in data mining. *Knowledge and Information Systems, 14*(1), 1-37. doi: 10.1007/s10115-007-0114-2

Yachi, S., & Loreau, M. (1999). Biodiversity and ecosystem productivity in a fluctuating environment: The insurance hypothesis. *Proceedings of the National Academy of Sciences, 96*(4), 1463–1468. doi: 10.1073/pnas.96.4.1463

Yang, M., & Kang, J. (2013). Psychoacoustical evaluation of natural and urban sounds in soundscapes. *The Journal of the Acoustical Society of America, 134*(1), 840-851. doi: 10.1121/1.4807800

York, J. E., Young, A. J., & Radford, A. N. (2014). Singing in the moonlight: dawn song performance of a diurnal bird varies with lunar phase. *Biology Letters*, *10*(1), 20130970. doi: 10.1098/rsbl.2013.0970

Young, A. M. (1981). Temporal Selection for Communicatory Optimization: The Dawn-Dusk Chorus as an Adaptation in Tropical Cicadas. *The American Naturalist, 117*(5), 826–829. doi: 10.1086/283770

Young, D., & Bennet-Clark, H. C. (1995). The Role of the Tymbal in Cicada Sound Production. *Journal of Experimental Biology*, *198*(4), 1001-1020. Retrieved from http://jeb.biologists.org/content/jexbio/1198/1004/1001.full.pdf.

Young, D., & Josephson, R. K. (1983). Pure-tone songs in cicadas with special reference to the genus Magicicada. *Journal of Comparative Physiology A, 152*(2), 197-207. doi: 10.1007/bf00611184

Zelick, R., & Narins, P. M. (1985). Characterization of the advertisement call oscillator in the frog Eleutherodactylus coqui. *Journal of Comparative Physiology. A, Sensory, Neural, and Behavioral Physiology, 156*(2), 223-229. doi: 10.1007/bf00610865

Zhang, L., Towsey, M., Xie, J., Zhang, J., & Roe, P. (2016). Using multi-label classification for acoustic pattern detection and assisting bird species surveys. *Applied Acoustics, 110*, 91-98. doi: 10.1016/j.apacoust.2016.03.027

Appendices

Appendix A: Accessibility of the Data and Code

Environmental recordings

1. Phillips, Y. (2018). Environmental long-duration audio recordings: Gympie and Woondum National Park. [Queensland University of Technology]. https://doi.org/10.4225/09/5a7297ee4b893.

Sample minutes – Supplementary information

2. Sample minutes – links to 1200 minutes and summary of the contents of each one-minute audio segment (Phillips et al., 2018). https://doi.org/10.1371/journal.pone.0193345.s004

Acoustic indices

3. Phillips, Y. (2018). Acoustic Indices: thirteen months at two sites (Gympie and Woondum National Park). [Queensland University of Technology]. https://doi.org/10.4225/09/5a72950590d20

Cluster list

4. Phillips, Y. (2018). Cluster List: Gympie and Woondum National Park. [Queensland University of Technology]. https://doi.org/10.4225/09/5a729602b9a51

False-colour spectrograms - Gympie and Woondum National Park

5. Phillips, Y. (2018). False-colour spectrograms – Gympie and Woondum National Park. [Queensland University of Technology]. https://doi.org/10.4225/09/5a729f04968ea

Sunrise and Sunset times - Gympie and Woondum National Park

6. Phillips, Y. (2018). Sunrise and Sunset times – Gympie and Woondum National Park. [Queensland University of Technology]. http://researchdatafinder.qut.edu.au/individual/n29753

Site Photos – Gympie and Woondum National Park

7. Phillips. Y. (2018). Photos of Audio Recording Sites – Gympie and Woondum National Park. [Queensland University of Technology]. https://doi.org/10.4225/09/5a7ce77feb9e9
8. Code is available at https://github.com/QutEcoacoustics/plos-visualization-paper/blob/master/scripts

Appendix B: Bird, Mammal, and Cicada Species at the Gympie and Woondum National Park Sites

The list of bird species listed below were initially identified by Yvonne Phillips and later verified by an experienced local birder. The links provided are to the calls that were verified on the Ecosounds (Truskinger, Cottman-Fields & Roe, 2017) website. One link is provided for each species from each site. If two links are provided for a species, the first is from the Gympie National Park and the second from the Woondum National Park. This is followed by a table containing the three mammal species annotated at each site. These calls are open-access under the creative commons licence see https://doi.org/10.4225/09/5a7297ee4b893. Popple (2006) was used to identify the cicada species.

Bird species	Gympie National Park	Woondum National Park
1. Australian owlet-Nightjar (*Aegotheles cristatus*) https://www.ecosounds.org/listen/353749?start=7945 http://www.ecosounds.org/listen/462768?start=1260	✓	✓
2. White-throated Nightjar (*Eurostopodus mystacalis*) http://www.ecosounds.org/listen/353628?start=5730	✓	
3. Tawny Frogmouth (*Podargus strigoides*) https://www.ecosounds.org/listen/354037?start=5427	✓	
4. Brown Cuckoo-Dove (*Macropygia amboinensis*) http://www.ecosounds.org/listen/333239?start=22140 http://www.ecosounds.org/listen/462847?start=10350	✓	✓
5. Peaceful Dove (*Geopelia striata*) http://www.ecosounds.org/listen/331712?start=23280 https://www.ecosounds.org/listen/462782?start=7800	✓	✓
6. Wonga Pigeon (*Leucosarcia picata*) http://www.ecosounds.org/listen/353659?start=22650	✓	✓
7. White-headed Pigeon (*Columba leucomela*) http://www.ecosounds.org/listen/353659?start=23250	✓	✓
8. Wompoo-fruit Dove (*Ptilinopus magnificus*) http://www.ecosounds.org/listen/462853?start=13830		✓
9. Bar-shouldered Dove (*Geopelia humeralis*) https://www.ecosounds.org/listen/353515?start=21805		✓
10. Laughing Kookaburra (*Dacelo novaeguineae*) https://www.ecosounds.org/listen/269829?start=22552	✓	✓
11. Rainbow Bee-eater (*Merops ornatus*) http://www.ecosounds.org/listen/461137?start=13110	✓	✓
12. Fan-tailed Cuckoo (*Cacomantis flabelliformis*) http://www.ecosounds.org/listen/333279?start=20730 http://www.ecosounds.org/listen/353654?start=19230	✓	✓
13. Brush Cuckoo (*Cacomantis variolosus*) https://www.ecosounds.org/listen/353016?start=4089 http://www.ecosounds.org/listen/353055?start=17220	✓	✓

Bird species	Gympie National Park	Woondum National Park
14. Channel-billed Cuckoo (Scythrops novaehollandiae) https://www.ecosounds.org/listen/462194?start=9180 http://www.ecosounds.org/listen/353075?start=14550	✓	✓
15. Shining Bronze Cuckoo (*Chalcites lucidus*) https://www.ecosounds.org/listen/461147?start=11100 http://www.ecosounds.org/listen/331870?start=22140	✓	✓
16. Eastern Koel (*Eudynamys orientalis)*) http://www.ecosounds.org/listen/353934?start=22140		✓
17. Little Bronze Cuckoo (Chalcites minutillus barnardi) http://www.ecosounds.org/listen/352910?start=21510		✓
18. Large-billed Scrubwren (*Sericornis magnirostra*) http://www.ecosounds.org/listen/353659?start=20910 http://www.ecosounds.org/listen/352933?start=16290	✓	✓
19. Brown Gerygone (*Gerygone mouki*) https://www.ecosounds.org/listen/331473?start=23190		✓
20. White-throated Gerygone (*Gerygone albogularis*) http://www.ecosounds.org/listen/354138?start=21540	✓	
21. Brown Thornbill (*Acanthiza pusilla*) http://www.ecosounds.org/listen/354380?start=21630		✓
22. Pied Butcherbird (*Cracticus nigrogularis*) https://www.ecosounds.org/listen/277079?start=11018	✓	
23. Grey Butcherbird (*Cracticus torquatus*) https://www.ecosounds.org/listen/333223?start=18906	✓	
24. Australian Magpie (*Cracticus tibicen*) http://www.ecosounds.org/listen/353659?start=20550 https://www.ecosounds.org/listen/461034?start=12900	✓	✓
25. Pied Currawong (*Strepera graculina*) http://www.ecosounds.org/listen/354371?start=12300 http://www.ecosounds.org/listen/277150?start=22050	✓	✓
26. Black-faced Cuckoo-shrike (*Coracina novaehollandiae*) https://www.ecosounds.org/listen/462915?start=3330	✓	
27. White-bellied Cuckoo-shrike (*Coracina papuensis*) https://www.ecosounds.org/listen/462194?start=12720	✓	
28. Cicadabird (*Coracina tenuirostris*) https://www.ecosounds.org/listen/353955?start=24210 http://www.ecosounds.org/listen/353339?start=21810	✓	✓
29. Varied Triller (*Lalage leucomela*) https://www.ecosounds.org/listen/333223?start=20916 https://www.ecosounds.org/listen/331835?start=6401	✓	✓
30. Eastern Whipbird (*Psophodes olivaceus*) https://www.ecosounds.org/listen/461137?start=13050 http://www.ecosounds.org/listen/352910?start=21870	✓	✓
31. Australian Logrunner (*Orthonyx temminckii*) https://www.ecosounds.org/listen/353515?start=17875		✓

Bird species	Gympie National Park	Woondum National Park
32. White-throated Treecreeper (*Cormobates leucophaea)* http://www.ecosounds.org/listen/331564?start=23130 http://www.ecosounds.org/listen/331835?start=5100	✓	✓
33. Red-browed Treecreeper (Climacteris erythrops) http://www.ecosounds.org/listen/353202?start=270		✓
34. Spangled Drongo (*Dicrurus bracteatus*) https://www.ecosounds.org/listen/354371?start=11839 http://www.ecosounds.org/listen/354038?start=17640	✓	✓
35. Leaden Flycatcher (*Myiagra rubecula)* https://www.ecosounds.org/listen/333223?start=18666 https://www.ecosounds.org/listen/331870?start=22018	✓	✓
36. Magpie-Lark (*Grallina cyanoleuca*) https://www.ecosounds.org/listen/461137?start=11220	✓	
37. Spectacled Monarch (*Symposiarchus trivirgatus*) http://www.ecosounds.org/listen/331712?start=23340 http://www.ecosounds.org/listen/352933?start=17160	✓	✓
38. Black-faced Monarch (*Monarcha melanopsis*) http://www.ecosounds.org/listen/353317?start=20160	✓	
39. Grey Fantail (*Rhipidura albiscapa*) http://www.ecosounds.org/listen/354259?start=20430 http://www.ecosounds.org/listen/462778?start=13440	✓	✓
40. Rufous Fantail (Rhipidura rufifrons) http://www.ecosounds.org/listen/354554?start=23100 http://www.ecosounds.org/listen/354042?start=17970	✓	✓
41. Australian Brush-turkey (*Alectura lathami*) http://www.ecosounds.org/listen/333333?start=18480 https://www.ecosounds.org/listen/353503?start=17687	✓	✓
42. Torresian Crow (*Corvus orru*) http://www.ecosounds.org/listen/354554?start=23400 http://www.ecosounds.org/listen/461034?start=11280	✓	✓
43. White-winged Chough (*Corcorax melanorhamphos*) http://www.ecosounds.org/listen/461260?start=10590	✓	
44. Mistletoebird (*Dicaeum hirundinaceum*) http://www.ecosounds.org/listen/333279?start=20880 https://www.ecosounds.org/listen/353202?start=13474	✓	✓
45. Red-browed Finch (*Neochmia temporalis*) http://www.ecosounds.org/listen/353546?start=20730 https://www.ecosounds.org/listen/333333?start=19530	✓	✓
46. Russet-tailed Thrush (*Zoothera heinei*) http://www.ecosounds.org/listen/354138?start=21180 http://www.ecosounds.org/listen/353766?start=20490	✓	✓
47. Variegated Fairy-wren (*Malurus lamberti*) https://www.ecosounds.org/listen/331730?start=20460		✓
48. Scarlet Honeyeater (*Myzomela sanguinolenta*) http://www.ecosounds.org/listen/277167?start=22530 http://www.ecosounds.org/listen/331862?start=19740	✓	✓

Bird species	Gympie National Park	Woondum National Park
49. White-throated Honeyeater (*Melithreptus albogularis*) http://www.ecosounds.org/listen/333239?start=22140 http://www.ecosounds.org/listen/352933?start=16440	✓	✓
50. Lewin's Honeyeater (*Meliphaga lewinii*) http://www.ecosounds.org/listen/354138?start=22170 https://www.ecosounds.org/listen/353202?start=5944	✓	✓
51. Yellow-faced Honeyeater (*Caligavis chrysops*) http://www.ecosounds.org/listen/461137?start=13140 http://www.ecosounds.org/listen/352942?start=16800	✓	✓
52. Noisy Friarbird (*Philemon corniculatus*) https://www.ecosounds.org/listen/276955?start=11400 https://www.ecosounds.org/listen/353735?start=10999	✓	✓
53. Noisy Miner (*Manorina melanocephala*) http://www.ecosounds.org/listen/353955?start=23760	✓	
54. White-naped Honeyeater (*Melithreptus lunatus*) https://www.ecosounds.org/listen/354091?start=21987	✓	
55. Olive-backed Oriole (*Oriolus sagittatus*) http://www.ecosounds.org/listen/352821?start=900		✓
56. Australasian Figbird (*Sphecotheres vieilloti*) https://www.ecosounds.org/listen/333333?start=19770	✓	
57. Masked Lapwing (Vanellus miles) http://www.ecosounds.org/listen/331587?start=20520		✓
58. Rufous Whistler *(Pachycephala rufiventris)* http://www.ecosounds.org/listen/331918?start=16860 http://www.ecosounds.org/listen/331838?start=24000	✓	✓
59. Golden Whistler *(Pachycephala pectoralis)* http://www.ecosounds.org/listen/331615?start=22680 https://www.ecosounds.org/listen/331835?start=671	✓	✓
60. Grey Shrike-thrush (*Colluricincla harmonica*) https://www.ecosounds.org/listen/333239?start=20070 http://www.ecosounds.org/listen/461034?start=11430	✓	✓
61. Crested Shrike-tit *(Falcunculus frontatus)* https://www.ecosounds.org/listen/333239?start=20070	✓	
62. Little Shrike-thrush (*Colluricincla megarhyncha*) http://www.ecosounds.org/listen/352933?start=15930		✓
63. Spotted Pardalote (*Pardalotus punctatus*) https://www.ecosounds.org/listen/461142?start=12870	✓	
64. Striated Pardalote (*Pardalotus striatus*) https://www.ecosounds.org/listen/331615?start=22407	✓	
65. Noisy Pitta (*Pitta versicolor*) https://www.ecosounds.org/listen/331644?start=19800 http://www.ecosounds.org/listen/462782?start=5400	✓	✓
66. Eastern Yellow Robin (*Eopsaltria australis*) https://www.ecosounds.org/listen/277132?start=18954 https://www.ecosounds.org/listen/352933?start=15868	✓	✓

Bird species	Gympie National Park	Woondum National Park
67. Rose Robin (*Petroica rosea*) http://www.ecosounds.org/listen/461142?start=12750	✓	
68. Green Catbird (*Ailuroedus crassirostris*) http://www.ecosounds.org/listen/277158?start=10800		✓
69. Satin Bowerbird (*Ptilonorhynchus violaceus*) https://www.ecosounds.org/listen/331879?start=1297		✓
70. Silvereye (*Zosterops lateralis*) http://www.ecosounds.org/listen/353339?start=18960		✓
71. Rainbow Lorikeet *(Trichoglossus haematodus moluccanus)* https://www.ecosounds.org/listen/353659?start=20550 http://www.ecosounds.org/listen/331862?start=23130	✓	✓
72. Little Lorikeet (*Glossopsitta pusilla*) http://www.ecosounds.org/listen/354007?start=17880 http://www.ecosounds.org/listen/353777?start=21540	✓	✓
73. Australian King-Parrot (*Alisterus scapularis*) http://www.ecosounds.org/listen/331508?start=22380 http://www.ecosounds.org/listen/352942?start=17070	✓	✓
74. Pale-headed Rosella (*Platycercus adscitus*) https://www.ecosounds.org/listen/276950?start=23460	✓	
75. Crimson Rosella (*Platycercus elegans*) http://www.ecosounds.org/listen/462847?start=8670		✓
76. Yellow-tailed Black-Cockatoo (*Calyptorhynchus funereus*) https://www.ecosounds.org/listen/277057?start=22200 http://www.ecosounds.org/listen/353777?start=21660	✓	✓
77. Sulphur-crested Cockatoo (*Cacatua galerita*) https://www.ecosounds.org/listen/333333?start=18330	✓	
78. Southern Boobook (*Ninox boobook*) http://www.ecosounds.org/listen/331618?start=20970 http://www.ecosounds.org/listen/331754?start=3780	✓	✓
79. Powerful Owl (*Ninox strenua*) http://www.ecosounds.org/listen/331564?start=21000	✓	
80. Sooty Owl (*Tyto tenebricosa tenebricosa*) http://www.ecosounds.org/listen/461034?start=3660		✓
TOTALS	**63**	**60**

Mammal species	Gympie National Park	Woondum National Park
1. Koala (*Phascolarctos cinereus*) https://www.ecosounds.org/listen/331907?start=12570 https://www.ecosounds.org/listen/333316?start=12393	✓	✓
2. Red Fox (*Vulpes vulpes)* https://www.ecosounds.org/listen/331667?start=11880	✓	
3. White-striped Free-tailed Bat https://www.ecosounds.org/listen/353571?start=6180 https://www.ecosounds.org/listen/353339?start=570	✓	✓
TOTALS	**3**	**2**

Cicada species	Gympie National Park	Woondum National Park
1. Bark Squeaker Cicada (*Pauropsalta corticinus*) https://www.ecosounds.org/listen/333331?start=3080	✓	
2. Large Bottle Cicada (*Glaucopsaltria viridis*) https://www.ecosounds.org/listen/352967?start=17691	✓	
3. Razor Grinder Cicada (*Henicopsaltria eydouxii*) https://www.ecosounds.org/listen/352967?start=18321 https://www.ecosounds.org/listen/353241?start=18919	✓	✓
4. Double Drummer Cicada (*Thopha saccata*) https://www.ecosounds.org/listen/461933?start=8010	✓	
5. Bladder Cicada (*Cystosoma saundersii*) https://www.ecosounds.org/listen/331845?start=17267 https://www.ecosounds.org/listen/462580?start=7020	✓	✓
6. Brown Bunyip Cicada (*Tamasa tristigma)* https://www.ecosounds.org/listen/352949?start=17097 https://www.ecosounds.org/listen/353079?start=17565	✓	✓
7. Black Tree-ticker (*Birrima varians*) https://www.ecosounds.org/listen/353132?start=9221		✓
8. Phantom Knight Cicada (*Psaltoda brachypennis*) https://www.ecosounds.org/listen/353379?start=11647		✓
TOTALS	**6**	**5**

Appendix C: Wildlife Camera Captures

A single Uovision Panoramic UV572 Wide Angle wildlife camera (Uovision Europe, 2014) was deployed at the two recording sites between the dates listed below. The single camera was moved between the two sites.

Site of deployment	Date	Number of triggers
Woondum National Park	14 February 2016 – 28 February 2016	1578
Woondum National Park	6 March 2016 – 13 March 2016	770
Gympie National Park	13 March 2016 – 27 March 2016	2304
Gympie National Park	3 April 2016 – 10 April 2016	1117
Woondum National Park	10 April 2016 – 24 April 2016	25
Woondum National Park	14 June 2016 – 3 July 2016	21
Gympie National Park	3 July 2016 – 24 July 2016	113

Note: All captures listed in the table below are videos except for captures marked (P), these were captured prior to the commencement of the video capture commencing on the 14 February 2016.

The camera was deployed at the two sites with the camera setting of video to record initially 10-second video, on the 3 April 2016 this was changed to a 15-second video and on the 3 July 2016 to 20 seconds of video. The camera was unbaited, and deployed at a height of between 0.4-0.9 metres above the ground by being strapped to a tree, and aimed horizontally. The camera at Woondum was re-positioned on the 10 April 2016 to a more sheltered position about 5 metres behind the audio recorder due to high number of false triggers previously. The list of species captured on the wildlife camera during February 2016 to July 2016 at the Gympie and Woondum National Park sites. The numbers indicate the count of the captures (additional counts within a 10-minute period are excluded) as described in Meek et al. (2014).

(P) denotes a photo rather than a video trigger, these relate to a couple of short deployments in January and February 2016 before the first video deployment.

Site	**Gympie National Park**			
Moon Phase	**First Quarter**	**Full Moon**	**Last Quarter**	**New Moon**
Species				
Australian Brush-turkey *(Alectura lantami*)	17 Jan 2016 (P) 5:36 pm (IMAG0877	20 July 2016 4:59 pm (IMAG0011	24 Jul 2016 6:21 am (IMAG0052	10 Apr 2016 9:08 am (IMAG102)
	18 Mar 2016 6:19 am (IMAG0643)	22 Jul 2016 3:27 pm (IMAG0020)		6 Jul 2016 6:25 am (IMAG0011)
	12 Jul 2016 9:26 am (IMAG0003)			
	12 Jul 2016 5:26 pm (IMAG0017)			
Australian Magpie (*Cracticus tibicen)*	17 Mar 2016 6:35am (IMAG0526)	21 Mar 2016 8:09 am (IMAG0018)		
		24 Mar 2016 6:17am (IMAG0298)		
		24 Mar 2016 3:28pm (IMAG0363		
Site	**Woondum National Park**			
Moon Phase	**First Quarter**	**Full Moon**	**Last Quarter**	**New Moon**
Species				
Australian Brush-turkey (*Alectura lantami)*	11 Apr 2016 7:28 am (IMAG0010)	24 Feb 2016 1:20 pm (IMAG0331)	27 Feb 2016 6:59 am (IMAG0633)	
	15 Apr 16 2:13 pm (IMAG0014)	24 Feb 2016 2:19 pm (IMAG0337)	27 Feb 16 6:27 pm (IMAG0685)	
	17 Apr 2016 6:10 am (IMAG0018)	18 Apr 16 1:55 pm (IMAG0003)		
	17 Apr 2016 4:45pm (IMAG0002)	20 Apr 2016 5:44pm (IMAG0005)		
Australian Magpie (*Cracticus tibicen)*				

Site	Gympie National Park			
Moon Phase	**First Quarter**	**Full Moon**	**Last Quarter**	**New Moon**
Species				
Common Brushtail Possum (*Trichosurus vulpecula*)	19 Jan 16 (P) 1:30 am (IMAG1339)	21 Mar 2016 12:53am (IMAG0017)		10 Apr 2016 1:02 am (IMAG1020)
		25 Mar 2016 1:38 am (IMAG0364)		
Echidna (*Tachyglossus aculeatus*)	16 Mar 2016 10:49 pm (IMAG0490)	17 Jul 2016 6:56 pm (IMAG0003)	3 Apr 2018 9:46 pm (IMAG0034)	
Eastern Whipbird (*Psophodes olivaceus*)				
Emerald Dove (*Chalcophaps indica)*				4 Apr 2016 8:13 am (IMAG0036)
Site	**Woondum National Park**			
Moon Phase	**First Quarter**	**Full Moon**	**Last Quarter**	**New Moon**
Species				
Common Brushtail Possum (*Trichosurus vulpecula*)				
Echidna (*Tachyglossus aculeatus*)				
Eastern Whipbird (*Psophodes olivaceus*)	16 Jun 2016 10:41 am (IMAG0012)			
Emerald Dove (*Chalcophaps indica)*				

Site	**Gympie National Park**			
Moon Phase	**First Quarter**	**Full Moon**	**Last Quarter**	**New Moon**
Species				
Grey Shrike-thrush (*Colluricincla harmonica*)		5 July 2016 2:56 pm (IMAG0008)		05 Jul 2016 2:56 pm (IMAG0008)
		18 Jul 2016 11:58 am (IMAG0005)		
		19 Jul 2016 3:51 pm (IMAG0008)		
Lewin's Honeyeater (*Meliphaga lewinii*)				
Lace Monitor (*Varanus varius)*		21 Mar 2016 8:52 am (IMAG0022)		
		22 Mar 2016 4:11 pm (IMAG0211)		
Rat species				12 Feb 2016 1:25 am (IMAG1536)

Site	**Woondum National Park**			
Moon Phase	**First Quarter**	**Full Moon**	**Last Quarter**	**New Moon**
Species				
Grey Shrike-thrush (*Colluricincla harmonica*)				
Lewin's Honeyeater (*Meliphaga lewinii*)	13 Apr 2016 12:53 pm (IMAG0012)			
Lace Monitor (*Varanus varius)*				
Rat species			30 Jun 2016 9:06 pm (IMAG0005)	

Site	**Gympie National Park**			
Moon Phase	**First Quarter**	**Full Moon**	**Last Quarter**	**New Moon**
Species				
Red-browed finch (*Neochmia temporalis*)				
Swamp Wallaby (*Wallabia bicolor*)	08 Jul 2016 8:34 pm (IMAG0037)	26 Mar 2016 7:17 am (IMAG0618)		06 Apr 2016 1:18 am (IMAG0285)
	09 Jul 2016 3:42 am (IMAG0038)	17 Jul 2016 4:38 am (IMAG0020)		08 Apr 2016 4:56 pm (IMAG0980)
	09 Jul 2016 7:03 am (IMAG0041)	18 Jul 2016 3:18 pm (IMAG0006)		06 Jul 2016 3:28 am (IMAG0010)
	16 Jul 2016 5:12 pm (IMAG0018)	19 Jul 2016 10:15 pm (IMAG0009)		08 Jul 2016 12:40 am (IMAG0020)
		20 Jul 2016 5:43 pm (IMAG0012)		08 Jul 2016 9:28 am (IMAG0028)
				08 Jul 2016 9:47 am (IMAG0030)
Site	**Woondum National Park**			
Moon Phase	**First Quarter**	**Full Moon**	**Last Quarter**	**New Moon**
Species				
Red-browed finch (*Neochmia temporalis*)	17 Apr 2016 7:55 am (IMAG0022)	19 Apr 2016 1:16 pm (IMAG0004)		
	16 June 2016 2:40pm (IMAG0011)			
Swamp Wallaby (*Wallabia bicolor*)		25 Feb 2016 6:40 pm (IMAG0466)	28 Jun 2016 8:50 am (IMAG0002)	
		26 Feb 2016 11:25 pm (IMAG0598)		
		17 Jun 2016 9:42 pm (IMAG0013)		

Site	Gympie National Park			
Moon Phase	**First Quarter**	**Full Moon**	**Last Quarter**	**New Moon**
Species				
Tawny Frogmouth (*Podargus strigoides*)	20 Jan 16 (P) 9:52 pm (IMAG3004)			
Torresian Crow (*Corvus orru*)	14 Mar 2016 11:19 am (IMAG0105)			
White-winged Chough (*Corcorax melanorhamphos*)	17 Mar 2016 7:57 am (IMAG0533)			
Eastern Yellow Robin (*Eopsaltria australis*)				
Wonga Pigeon (*Leucosarcia picata*)	14 Mar 2016 5:13 pm (IMAG0148)			
Yellow-footed Antechinus (*Antechinus flavipes flavipes*)			03 Apr 2016 11;48pm (IMAG0035)	
TOTALS	**15**	**18**	**3**	**12**
Site	**Woondum National Park**			
Moon Phase	**First Quarter**	**Full Moon**	**Last Quarter**	**New Moon**
Species				
Tawny Frogmouth (*Podargus strigoides*)				
Torresian Crow (*Corvus orru*)				
White-winged Chough (*Corcorax melanorhamphos*)				
Eastern Yellow Robin (*Eopsaltria australis*)				07 Feb 16 (P) 9:15 am (IMAG0258)
Wonga Pigeon (*Leucosarcia picata*)				
Yellow-footed Antechinus (*Antechinus flavipes flavipes*)				
TOTALS	**8**	**8**	**4**	**1**

Appendix D: Cluster Labels and Sizes

The number of each of the quiet clusters at each of the two recording sites. The numbers are in minutes.

Cluster	Acoustic class	Gympie	Woondum	Totals	Rank size
1	Insects	6,444	3,249	9,693	18
2	Light rain and birds	7,091	9,600	16,691	22
3	Birds (Low calling rate)	16,020	9,167	25,187	12
4	Insects and birds	17,521	10,813	28,334	11
5	**Fairly quiet**	**27,503**	**8,942**	**36,445**	**8**
6	Mostly quiet	2,883	1,640	4,523	52
7	Cicadas & birds & wind	10,702	10,208	20,910	16
8	Cicadas & birds & wind	18,210	4,673	22,883	13
9	**Moderate Wind**	**21,958**	**27,949**	**49,907**	**6**
10	Light to Moderate rain	3,723	9,138	12,861	32
11	**Birds**	**35,945**	**38,457**	**74,402**	**3**
12	Cicadas	1,659	1,320	2,979	58
13	**Quiet**	**33,692**	**50,310**	**84,002**	**1**
14	Birds	3,683	804	4,487	53
15	**Birds**	**20,245**	**11,345**	**31,590**	**9**
16	Cicadas	6,352	1,740	8,092	44
17	Light Rain or insects [IC]	5,069	12,957	18,026	21
18	Moderate rain	4,073	5,522	9,595	38
19	Moderate wind	11,580	3,904	15,484	24
20	Moderate wind	3,950	17,562	21,512	15
21	Light rain	1,171	6,961	8,132	43
22	**Insects and birds**	**27,000**	**47,630**	**74,630**	**2**
23	Aircraft, motorbikes, thunder	2,690	1,134	3,824	54
24	Wind and/or cicadas [IC]	6,175	4,030	10,205	36
25	Wind	8,175	16,519	24,694	13
26	Insects and wind	1,778	5,179	6,957	48
27	Insects	11,494	4,954	16,448	23
28	Birds and/or insects or aircraft [IC]	11,158	3,030	14,188	28
29	**Insects**	**33,867**	**27,796**	**61,663**	**5**
30	Birds and Quiet	11,222	7,196	18,418	20
31	**Quiet**	**13,150**	**25,367**	**38,517**	**7**

Cluster	Acoustic class	Gympie	Woondum	Totals	Rank size
32	Cicadas	9,164	4,637	13,801	30
33	Birds	14,893	3,930	18,823	18
34	Cicadas	3,814	5,449	9,263	40
35	**Quiet**	**17,113**	**50,457**	**67,570**	**4**
36	Quiet and/or aircraft IC	8,258	4,022	12,280	33
37	**Birds (morning chorus)**	**17,011**	**14,301**	**31,312**	**10**
38	Quiet	3,835	11,016	14,851	26
39	Birds and aircraft	11,897	1,938	13,835	29
40	Wind and/or birds or insects IC	8,594	11,039	19,633	17
41	Very quiet	4,437	1,063	5,500	50
42	Strong wind	4,591	2,602	7,193	47
43	Birds (morning chorus)	3,324	4,168	7,492	46
44	Loud cicadas	3,858	7,223	11,081	35
45	Wind and aircraft	2,767	613	3,380	56
46	Wind	2,333	5,594	7,927	45
47	Strong wind	10,032	4,600	14,632	27
48	Cicadas	3,901	11,044	14,945	25
49	Aircraft (including thunder)	2,173	1,025	3,198	57
50	Quiet and insects and birds IC	1,766	3,180	4,946	51
51	Strong wind	4,708	4,253	8,961	41
52	Wind	16,324	2,413	18,737	19
53	Mostly quiet	6,378	204	6,582	49
54	Moderate rain and birds	1,445	11,589	13,034	31
55	Quiet	8,208	1,211	9,419	39
56	Wind	6,419	2,228	8,647	42
57	Birds or wind IC	745	1,585	2,330	59
58	Loud birds	3,121	423	3,544	55
59	Moderate rain	782	10,707	11,489	34
60	Rain or birds	276	1,187	1,463	60
TOTALS		**568,350**	**572,797**	**1,141,147**	

The difference between the totals between the Gympie National Park site and the Woondum National Park site is mainly due to the removal of three days of recording on the 28 to the 30 October 2015 at Gympie National Park site. The highest ten ranked clusters in terms of the number of instances are in bold, four are quiet clusters, three are bird clusters, two are insects, and there is one wind cluster.